Essays on empirical industrial organization

Fernandez Machado, Roxana

Publication date:
2017

Document Version
Publisher's PDF, also known as Version of record

Link to publication in Tilburg University Research Portal

Citation for published version (APA):
Fernandez Machado, R. (2017). *Essays on empirical industrial organization: Entry and innovation*. CentER, Center for Economic Research.

ESSAYS ON EMPIRICAL INDUSTRIAL ORGANIZATION: ENTRY AND INNOVATION

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PROEFSCHRIFT

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof.dr. E.H.L. Aarts, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Ruth First zaal van de Universiteit op

dinsdag 29 augustus 2017 om 16.00 uur

door

ROXANA CECILIA FERNÁNDEZ MACHADO

geboren te Lima, Peru.

PROMOTOR:	prof. dr. J. Boone
COPROMOTOR:	dr. T.J. Klein
PROMOTIECOMMISSIE:	prof. dr. J. Abbring
	dr. L. Filistrucchi
	dr. F. Schuett
	prof. dr. F. Verboven

To Luisa Arteaga, my grandma.

Acknowledgements

First and foremost, I would like to heartedly thank my co-promotor Tobias Klein. Tobias, throughout these years I have learned a lot from your enthusiasm for economic research, your critical way of thinking, and your dedication in achieving excellence in every outcome. You have patiently taught me how to improve my writing and presentation skills, while constantly encouraged me to explore new ideas. Thank you for your unconditional support, which has been crucial in taking my Ph.D. to a good end. Second, I would like to thank my promotor, Jan Boone, who has been at all times supportive and has given me his advice anytime I needed it. I would also like to acknowledge the valuable input of Catherine Schaumans, who introduced me to the world of entry models and provided me guidance in the beginning of my Ph.D. Furthermore, I would like to thank the members of my doctoral committee for taking the time to read my thesis and share their insightful comments: Jaap Abbring, Lapo Filistrucchi, Florian Schuett and Frank Verboven.

During these years, I have greatly benefited from being part of an excellent academic environment at Tilburg University. I have had the privilege of being surrounded by faculty members always willing to help us students in developing our own piece of work. In particular, I am deeply grateful to Jaap Abbring for his numerous advices and constant support, especially during the job market period. I would also like to thank Florian Schuett for always being willing to help me and for taking the time to provide me detailed feedback. Furthermore, I would like to thank Cedric Argenton, Bettina Drepper, Lapo Filistrucchi and Sigrid Suetens, who were at all times thoughtful and supportive. My gratitude also extends to Otilia Boldea, Jochem de Bresser, Patricio Dalton and Burak Uras, who advised me in multiple occasions before traveling to Chicago for the job market. Finally, I would like to devote especial thanks to Korine de Bor, Ilse Streng, Maartje van Genk and Cecile de Bruijn, who have always been kind and helpful with many administrative issues.

The innumerable hours I spent at the university allowed me to meet fantastic people. I would like to express my deep gratitude to my classmates: Alaa, Aida, Bálint, Bo, Camilo, Clemens, Consuelo, Loes, Michal, Moritz, Renata, Sebastian, Serena, Víctor, and Yufeng. You all have been an endless source of encouragement, fun, and companionship. In particular, I would like to thank Yan Xu for sharing with me her continuous willingness to learn, which has inspired me multiple times.

On a personal note, I owe a huge thanks to my best friends Bárbara and Caro, who have always been caring and supportive, especially when things did not progress very smoothly. Thanks for your endless affection. Sandra and Paul, thanks for letting me be part of your precious home and for all the things you have shared with me. I feel truly fortunate and happy to have you in my life. And Cata and Mitzi, you have been the best housemates and friends one could ever wish for. I would also like to thank Byron, Cassandre, Charlotte, Elise, Gissella, Ina, Isa, Lisanne and Rafi. I treasure every kind gesture that you all have had with me during all this time. Also, I am lucky to have a precious group of friends back home in Lima who through all these years abroad have remained present and have always been happy to welcome me back. This team is made up by: Carla, Claudia B., Claudia S., Cris, Mex, Nori, Pame and Vero.

Last but not least, I want to thank my parents, Pepe and Vicky, my brother, Martín, and my sister-in-law, Marina, who have always been there to celebrate each one of my triumphs and to encourage me to reach my goals. Lograr este proyecto tan importante para mí no hubiera sido posible sin su apoyo incondicional y su cariño infinito. In the seven years that have passed since I left Lima, my niece, Mariana, and my nephew, Marcelo, have joined our family. Mariana and Marcelo, you have brought pure joy and love to our family and I miss you every single day. Finally, I would like to thank my grandma, Luisa, who just turned 104 years old. She has always been an example of determination and strength to me. Luisa is a woman ahead of her time and I am immensely proud of how much she has achieved. Abu, cada vez que voy a casa me preguntas por mi tesis y, por tanto, te la dedico con mucho amor.

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1 | Introduction

This dissertation contains three essays on empirical industrial organization devoted to studying firms' strategic interaction in different settings. The first two essays concentrate on firms' entry decisions; they address questions related to spillover effects of entry and first-mover advantages, respectively. The third essay focuses on innovation and firms' patent portfolio choices. All essays are independent studies and analyze the mentioned topics using data from different industries.

The first essay (Chapter 2) presents an entry model that addresses an important matter in the area of urban economics: the development of cities. Over the last decades, the success of cities has hinged on their ability to become centers of consumption. Encouraging firms to settle and to provide a rich variety of services is therefore central for increasing the liveliness of cities. However, firms consider potential spillover effects generated by other market players when deciding whether or not to enter the market. This chapter focuses on the food and beverage service industry in the Netherlands, and investigates to what extent the presence of urban amenities produces positive spillovers on other amenities in the market. Using a unique dataset on firms' revenues and the number of market participants, the study extends previous entry models and simultaneously estimate a static two-type entry model with revenue equations. The model controls for unobserved characteristics that can be erroneously interpreted as spillovers. It also allows for product differentiation. I find that for the case of take-out places and bars, spillover effects upon entry are mainly unidirectional: the entry of bars positively affects the profitability of take-out places, but not vice versa. This shows evidence that different amenity services may have asymmetric effects on other amenities when entering the market. Taking into account this asymmetry is relevant for both new entrant firms and policy makers.

Chapter 3 presents structural entry models to analyze the competitive dynamics of firms in the presence of first-mover advantages. First-mover advantages arise due to direct network effects, switching costs and economies of scale. Competition authorities and regulators care about the consequences of such advantages since they can potentially deter entry. Using data from the U.S. digital mobile markets, the study empirically estimates a static two-type entry model. This allows to quantify the advantage early movers have relative to later entrants. The measure used is the impact of competitors' entry on the profits of incumbents and entrants. Controlling for market characteristics, the results show an asymmetric competitive effect in favor of incumbents. These results have implications for policy makers who seek to promote effective competition in local mobile markets.

Patent portfolios have become an important tool for firms to compete and secure their position in the market. However, the existing empirical literature has largely ignored the role of portfolio composition as an instrument to explain firms' strategic behavior. Chapter 4 shows how firms of different sizes choose their technologies in relation to other firms. The main goal of this study is to shed light on the underlying mechanisms driving the observed evolution of firms' patent portfolios. It uses data from the U.S. semiconductor industry to model the probability that firms of different sizes invest in a technology depending on the presence of other firms. The semiconductor industry provides an excellent setting given its rapid pace of technological change and the complexity of their technologies making firms heavily interrelated. The results show that firms of different sizes follow different patenting strategies. Small- and medium-size firms seem to replicate large firms' choices while ignoring the giants in the market. Furthermore, giants' portfolios are positively related to their previous investments, and they are overall independent of other types' choices. Finally, by characterizing each firm's relative portfolio position with respect to the giants, the study finds that firms that diversified their portfolio in different fields have not invested in more patents than the ones that follow giants' technological choices more closely.

2 | Spillover effects and city development

2.1 Introduction

Urban amenities -such as restaurants and bars- are recognized as important drivers of urban development. In the last decades, the role of cities as centers of consumption has grown, and the provision of a rich variety of services has become critical to determine the attractiveness of particular areas (Glaeser et al. (2001), Duranton and Puga (2014)). Accordingly, city planners design urban space with the goal to encourage firms to settle and make cities more attractive. Therefore, understanding strategic interactions among different amenities and the potential spillover effects of new entries has become paramount for policymakers wishing to encourage local economic development. This becomes especially relevant at times of limited municipal budgets when new tools need to be developed to assess the effectiveness of alternative incentive programs.

In this paper, I shed new light on the strategic interactions between different types of amenities. To this end, I analyze the food and beverage service industry, particularly cafeterias (take-out places)[1] and bars across local markets within cities in the Netherlands. I measure to what extent firms' entry decisions affect each other's profitability by further building upon the extensive empirical literature on entry. For this, I estimate a static entry model with revenue equation. Using the estimated structural parameters, I analyze how cities can best encourage firms to enter, thereby stimulating the liveliness of particular areas. To highlight the importance of designing policies that take into consideration the magnitude of spillover effects, I first conduct a policy experiment in which a tax relief is exclusively given to either cafeterias or bars.

[1] I use the term cafeteria to generally define all sort of take-away food places. The type of establishments considered under this name are listed in Section 2.2.2.

Second, provided that policymakers need resources to support these programs, I analyze the effectiveness of two different redistribution schemes (across and within cities) to increase the provision of amenities, especially in small cities where fewer firms are present.

I estimate the model using Dutch administrative data at the market level. These rich data not only contain information on the number of bars and cafeterias, but also on the average revenue per type of business in each local market. I also use census data on the corresponding demographic characteristics, such as population, density of houses and per capita income, among others, to control for observable market characteristics that motivate firms to enter.

This paper relates to the work by Schaumans and Verboven (2008, 2015), and Ferrari et al. (2010). First, I use the one-type model with demand equation developed by Ferrari et al. (2010) and Schaumans and Verboven (2015) as the baseline model to present preliminary evidence on the existence of spillovers of entry between both amenities services. I estimate the model for each service separately, taking the number of firms of the other type as exogenously given. This, however, does not account for unobserved factors that may drive the decision to enter for both types, and results may therefore be biased. To overcome this problem, I contribute to the literature on entry models by extending the baseline model to two types (cafeterias and bars). Modelling the entry decisions of both cafeterias and bars allows me to explicitly control for unobserved market characteristics, which results in a more precise estimation of spillover effects. Additionally, the advantage of including revenue equations is that it enables me to obtain unbiased estimates of competitive effects when firms offer differentiated services, as it is usually the case for consumption amenities.

This paper also relates to the literature on entry and spillover effects in the context of chain stores (see Yang (2012, 2016) and Toivanen and Waterson (2005) for an application to hamburger chain stores, and Holmes (2011) and Jia (2008) for the discount retailing industry). The arguments presented by these studies to justify the existence of spillovers, such as learning and economies of density, do not generally apply to other industries. In many local services, like the ones I study, single-establishment stores are the main market players. I contribute to this literature by providing evidence and additional insights on the existence of spillover effects for those types of industries.

My findings suggest that there exist quantitatively important effects of the number of bars on cafeterias' entry decisions. At the same time, the number of cafeterias do not significantly affect bars' profitability. This indicates that spillover effects of entry may be observed in only one direction. A possible explanation for this asymmetric result might be related to consumers' behavior and the consequent decrease of advertisement costs. People, when going out, primarily search for places that facilitate social interactions. Bars, in contrast to cafeterias, provide the space for people to socialize. The generation of foot-traffic due to bars' presence benefits cafeterias by lowering entry costs, such as advertising. A cafeteria might need to advertise less to inform people about its presence when bars are located nearby.

It is worth mentioning that the difference between the estimated spillover effects of the full model and the ones based on the baseline (one-type) model confirms the importance of incorporating a second type. The baseline model erroneously overestimates the effect of cafeterias' entry on bars' profitability. Mistakenly assuming that spillovers are symmetric (or that they do not exist) leads to the design of less effective urban policies.

Additionally, in line with the literature on entry (Bresnahan and Reiss (1991a), Mazzeo (2002)), I find that the entry of the first two competitors of the same type has the biggest negative effect on firms' profitability. The competitive effect is larger for bars than for cafeterias, which indicates that bars are less differentiated than cafeterias in the provision of services.

To demonstrate the importance of accounting for spillover effects in the design of urban policies, I simulate the effects of providing monetary incentives to only one type of amenity. Cities have traditionally tried to attract businesses by offering them tax breaks and other cash incentives. Therefore, using the estimates of my model, I evaluate how a tax relief that increases revenues by 25% affects entry. The results show that targeting incentives toward amenities that create the largest spillover effects is more effective -in terms of geographic coverage and number of firms-, especially if the objective is to increase amenities in less attractive markets. For instance, providing a tax relief to bars increases the coverage of services such that 17% of the markets that did not have either bars or cafeterias, they now have at least one of the services. This constitutes a greater effect compared to the one induced by a tax relief given to cafeterias (10%).

Over the past few years, domestic migration towards big cities has become more pronounced in the Netherlands (PBL (2013)). This can eventually be detrimental for less mobile people living in small cities, such as elderly and poorer people, if the offer of amenities decreases in response to this migration. In times of fiscal constraint, policymakers need to create innovative ways of securing funds that permits the provision of incentives in favor of less attractive urban areas. Conforming with this, in 2015 the Dutch Government announced its plan to send the *Dutch Urban Agenda* (or *Agenda Stad)* to parliament. The Agenda promotes, among other things, the cooperation within and between urban regions.[2] This motivates my second policy experiment in which I analyze the implications of different redistributive policies with the goal

[2]http://agendastad.nl/about-us/

of increasing firms' entry in small cities. I find that it is more effective to redistribute funds within cities (from big to small markets) than across cities (from big to small cities).

The rest of this paper is structured as follows. Section 4.3 describes the data. Section 2.3 presents the baseline model and provides preliminary evidence on spillover effects. Section 2.4 describes the full two-type model and estimation strategy. Section 2.5 discusses the results of the model and Section 2.6 presents the results of counterfactual simulations. Section 2.7 concludes with a brief summary of the main findings.

2.2 Data

This study investigates the strategic interaction between bars and cafeterias (take-away food places) using a cross sectional data set of small local markets in the Netherlands. The data used in this study are constructed from different sources and contain information on the total number of cafeterias and bars (N_C, N_B) and their respective average revenues per firm and per capita (r_C, r_B) in each local market. It also includes population (S) as a proxy for market size, and other demographic information (X) that may explain firms' entry decisions. In this section, I first present the market definition. Next, I explain in more detail the type of establishments I use for the study. Finally, I present an overview of demographic data.

2.2.1 Market definition

In 2010, the Netherlands was divided into 431 municipalities, which on average contained 9 postal codes (at 4-digit level). The market definition I use is slightly bigger than 4-digit postcode areas. Since information at postcode level was not available due to confidentiality of revenue data, based on location, a total of 3,810 4-digit postal codes were clustered into 2,780 local markets.[3] Since my objective is to measure spillover effects in the context of local services, having data at such disaggregated level represents an advantage.

Additionally, I make three main adjustments to the data. First, to mitigate problems with overlapping markets, I exclude big cities from my sample and only keep municipalities with less than 35,000 people. This leaves me with a total of 301 municipalities, which constitutes 70% of the total number.[4]

[3] More precisely, postcode areas were clustered into groups of up to 7 postal codes per market, according to distances between postcodes (on average 2 km away). This clustering process was performed using information provided in Google Maps on the XY-coordinates of the center of all Dutch postcodes.

[4] The average population size at municipality level is 38,500 inhabitants, so I take a conservative threshold to

Second, zoning regulation may prohibit firms from operating in certain local markets. As Datta and Sudhir (2013) show, the omission of zoning restrictions on entry leads to biased estimates of the factors affecting market potential and competitive intensity. Since I do not have good quality data on zoning restrictions, I partially control for this problem by excluding markets with zero retail locations. In that way, I ensure that purely residential areas are not part of my sample (Igami and Yang (2016) use a similar strategy). This, however, does not rule out the possibility that some municipalities may restrict the entry of a specific type of business, e.g. bars, in certain markets. As far as I know, permissions are given on a case by case basis. Unfortunately, I do not have information about those decisions and it is not possible for me to incorporate such cases in my model.

Finally, as I explain in more detail in the next subsection, I model the entry decision of single-establishment firms. Therefore, to avoid problems for not accounting for the presence of chain stores, I exclude from my sample markets in which chains are located. Given that chain stores in the Netherlands are typically located in busy urban areas, excluding these markets also allows me to correctly measure spillover effects. Consumer demand might be higher in markets with more foot-traffic or higher-quality commercial places. These unobserved attributes could lead to co-location of services, which the model would erroneously attribute to spillovers. Therefore, by excluding these markets I avoid misspecification errors.[5] There are some cases in which chain stores locate in highway rest areas.[6] The exclusion of these markets does not represent a problem since they are not of interest in the context of city development. After all these exclusions, the number of observations is reduced to 1,005 markets.

2.2.2 Establishment characteristics

The total number of retailers and their respective location were obtained from the General Business Register (*Algemeen Bedrijven Register*), collected by the Dutch Central Bureau of Statistics (CBS). The number of cafeterias contains all businesses registered by 2010 under the Dutch Standard Industrial Classification (SBI 2008) code '56102'.[7] According to this classification, cafeterias include snack bars and all sorts of fast-food takeaways: sandwich shops ("Brood-

ensure the exclusion of highly dense urban areas.

[5]As a robustness check, I also exclude city centers from my sample. I explain this in more detail in Section 2.5.

[6]These are areas where drivers and passengers can rest, eat, or refuel without exiting onto secondary roads. These areas are usually far from cities.

[7]The Dutch Standaard Bedrijfsindeling (SBI 2008) is based on the activity classification of the European Union (NACE) and on the classification of the United Nations (ISIC).

Table 2.1: Number of bars and cafeterias per type of establishment

	N. bars	%	N. cafeterias	%
Single-establishment firms	11,049	86	9,626	84
Small businesses (2 to 10 establishments)	1,632	13	1,608	14
Chain stores	139	1	194	2
Total	12,820		11,428	

Note: Information on the total number of bars and cafeterias in the Netherlands. Businesses are classified according to their number of establishments. *Source:* Dutch Central Bureau of Statistics.

jeszaken"), French fries shops, small businesses selling fried fish, pancakes and typical Dutch snacks. It also includes quick buffets, and all kind of take-out eating places. The category does not include restaurants, takeaways that belong to restaurants or ice-cream stores. Catering services are also not part of it.

Bars' SBI code is '5630' and it groups all types of bars (with and without dance halls), nightclubs, and beer houses. It also includes coffee shops (not in conjunction with the sale of soft drugs) and tearooms. Note that all businesses need to be registered before opening to the public.

The reason I focus on these consumption amenities is to ameliorate the presence of the so called global competitors in the literature on entry models. Including global competitors imposes additional challenges to measure the competitive interaction among firms. Compared to restaurants, for example, cafeterias and bars compete in relatively small geographical markets (local competition). It is more likely that people looking for a certain type of food (or quality of restaurant) decide to travel longer distances than when searching for bars and take-away food.

Moreover, I concentrate on single-establishment firms. On the one hand, they are very important for this sector: approximately 85% of the total number of stores are single-establishment (see Table 2.1). On the other hand, chain stores' entry decisions include additional features, e.g. cannibalization of own profits and economies of scale, that I am not able to cover since I do not observe firms' identity.

2.2.3 Market characteristics

Demographic data were obtained from the 2010 Census. I convert the data from its most disaggregated level (neighborhood) to the market level definition. As Table 2.2 shows, each market in my sample contains on average approximately 4,600 residents, of which a large percentage

Table 2.2: Summary statistics for the estimation sample

Variable	Mean	Std.Dev.	Min.	Max.
Population	4,641	3,396	320	18,010
Density (# of addresses per km^2 within a circle of 1km)	1,801	2,910	24	26,469
Fraction of households with children	0.40	0.06	0.20	0.67
Fraction of population under age of 14	0.18	0.03	0.11	0.37
Fraction of population between age of 15 and 24	0.11	0.02	0.05	0.20
Fraction of population between age of 25 and 44	0.24	0.03	0.11	0.39
Fraction of population between age of 45 and 64	0.30	0.03	0.10	0.49
Fraction of population over 65	0.16	0.04	0.03	0.38
Income per capita (000's eur)	21.29	3.49	12.95	61.40
Total retail locations	231	198	20	1,165
N. of supermarkets within a 3km radius	2.46	2.35	0.00	18
N. of observations				1,005

Note: The table shows the demographic information I include as control variables in my model. Population size is presented in levels for expository purposes in this table. *Source:* Census 2010.

is between the ages of 45 and 64 years old. The total number of retail locations, which is used to control for heterogeneity in retail activity across markets, shows a lot of variation. I also include the number of supermarkets to account for possible substitution between supermarket's products and the ones offered by take-out places and bars.

Table 3.1 reports counts of the observed market configurations (N_C, N_B) across the markets in my sample. There is quite a lot of variation in the market configuration. There are 98 markets without bars or cafeterias. The most frequent configuration consists of one bar and zero cafeterias. In general, there exists a positive correlation of 0.61 between the number of bars and cafeterias.

Finally, the bottom part of Table 3.1 presents the average per capita revenues of cafeterias and bars for those markets where a positive number of firms is observed. Compared to cafeterias, bars have slightly larger revenues with an average per capita level of 48.8.

2.3 Baseline model

The primary objective of this section is to present the baseline model and show preliminary evidence on the existence of spillover effects between the two types of amenities. To this end, I simultaneously estimate the one-type entry model with revenue equation (Schaumans and Verboven (2015), Ferrari et al. (2010)) for cafeterias and bars separately, treating entry decisions

Table 2.3: Number of firms and per capita average revenue

Cafeterias/Bars	0	1	2	3	4	5	6	7	8	9	10+	**Total**
0	98	83	52	30	11	6	2	1	1	0	0	284
1	48	56	53	38	17	7	7	1	2	1	0	230
2	20	40	33	31	19	10	6	2	0	1	1	163
3	9	17	25	19	11	5	6	3	1	1	0	97
4	5	8	12	8	5	11	6	1	2	2	2	62
5	1	7	8	8	7	1	2	4	2	2	9	51
6	5	1	6	3	5	1	5	4	1	1	6	38
7	0	2	2	1	1	3	3	3	3	0	4	22
8	0	0	0	3	2	3	4	2	1	0	4	19
9	0	0	0	2	1	0	0	3	2	1	5	14
10+	1	0	0	3	3	1	3	4	1	0	9	25
Total	187	214	191	146	82	48	44	28	16	9	40	1,005

Revenues per firm and per capita (sample of markets with N>0)	**Mean**	**Std.Dev.**
Cafeterias (eur)	42.2	34.8
Bars (eur)	48.8	39.3

Note: This table presents counts of the different market configurations (N_C, N_B) observed in my sample. *Source:* Dutch Central Bureau of Statistics.

of the other type as exogenously given. The results motivate further analysis to better understand the role of spillovers. They also constitute a stepping stone to build the assumptions of the extended two-type version of this model. Furthermore, based on the estimates, I calculate entry thresholds that are commonly used in entry models as competitive measure. They will serve as a benchmark to clearly show the importance of modelling the entry decisions of the other type. The reader already familiar with this methodology can skip the description of Section 2.3.1 and jump directly to the discussion of results in Section 2.3.2.

2.3.1 Simultaneous entry and revenue model

A firm maximizes profits under complete information and decides whether or not to enter the market. I assume there is free entry since my sample only contains areas where there is commercial activity, ruling out purely residential areas (see Section 2.2.1). This means that firms enter if and only if it is profitable. The entry decisions are summarized by the total number of firms entering the market, N. Firms are not assumed to be identical, as in Bresnahan and Reiss's model, but it is assumed that they are in a symmetric price equilibrium $p(N)$.

I first define the variable profits per firm and per capita by $v(N) \equiv (p(N)-c)q(p(N),N)$, the revenues per firm and per capita by $r(N) \equiv p(N)q(p(N),N)$, and the percentage markup or Lerner Index by $\mu(N) \equiv (p(N)-c)/p(N)$. The level of profits per firm, $\Pi(N)$, is not observed and it is typically modeled as a function of $v(N)$, market size S and fixed costs f. Provided that I observe $r(N)$ in each local market, $v(N)$ can be disentangled into two components such that:

$$\Pi(N) = \underbrace{\mu(N)\, r(N)}_{v(N)} S - f,$$

where the level of markups and the fixed costs component are unobserved.

Following standard entry models, I assume entry decisions are strategic substitutes, which means that an additional competitor will decrease a firms' marginal profits from entering ($v'(N) < 0$). If a firm decides not to enter, its payoffs are normalized to zero. Under the free entry condition, when observing N cafeterias (bars) one can infer that the market can only support N but not $N+1$ cafeterias (bars). This leads to the Nash equilibrium condition:

$$\mu(N+1)\, r(N+1)\, S - f < 0 < \mu(N)\, r(N)\, S - f,$$

or, in its equivalent logarithmic form:

$$\ln \frac{\mu(N+1)}{f} + \ln r(N+1) + \ln S < 0 < \ln \frac{\mu(N)}{f} + \ln r(N) + \ln S. \tag{2.1}$$

This equation can be estimated by using an ordered probit model. However, given that firm per capita revenues $r(N)$ are observed, I separately specify an equation for revenues and markups. I start by defining the logarithmic specification for per capita revenues as a function of market characteristics X, and the number of competitors N. Since my main goal is to find preliminary evidence on how different types of amenities strategically interact in the market, I also include the number of firms of the other type, N_j, assuming it is exogenously given. Furthermore, I control for unobserved market-specific demand shocks ξ. Then the revenue equation is specified as follows:

$$\ln r(N) = X\lambda + \alpha^N + \frac{\delta^{N_j}}{N} + \xi. \tag{2.2}$$

The parameters α^N and δ^{N_j} are fixed effects measuring the effect of entry of the N-th same-type and different-type of firm, respectively. This is a more flexible specification compared to the one used by several studies, in which the entry effect for every additional market participant is the same (αN or δN_j). To account for the fact that the impact of an other-type firm is spread out over the installed market participants, I divide the δ^{N_j} by N. Intuitively, if one additional bar attracts more people to the area, the impact over cafeterias' sales will depend on the available number of cafeterias. For instance, if there is only one cafeteria, those who want take-away food after having a drink will end up going to the only available option in the area. However, if two cafeterias are located nearby, I assume people have different preferences and will uniformly split among the two firms.

I specify the ratio of markups over fixed costs as a function of observed market characteristics X, entry fixed effects (τ^N and ρ^{N_j}), and an unobserved market-specific error term η. Contrary to the previous equation, I do not divide the effect of entry of a different-type firm by N. The intuition behind is that changes on a firm' net markups or costs cannot be shared with other firms in the market.

$$\ln \tfrac{\mu(N)}{f} = X\varphi + \tau^N + \rho^{N_j} - \eta. \tag{2.3}$$

Substituting both equations (2.2 and 2.3) in the profit equation, the entry condition (2.1) is written as

$$X\beta + \ln S + \theta^{N+1} + \gamma^{N_j} < \omega < X\beta + \ln S + \theta^N + \gamma^{N_j}, \tag{2.4}$$

where

$$\begin{aligned} \beta &\equiv \lambda + \varphi, \\ \theta^N &\equiv \alpha^N + \tau^N, \\ \gamma^{N_j} &\equiv \frac{\delta^{N_j}}{N} + \rho^{N_j}, \\ \omega &\equiv \eta - \xi. \end{aligned}$$

Since entry decisions are strategic substitutes, then $\theta^N > \theta^{N+1}$, that is, a firm's payoffs are decreasing in the number of firms. The potential spillover effects between different type of amenities are given by the estimated fixed effects γ^{N_j}, and their increasing or decreasing pattern will be an indication of the type of strategic interaction there exists between both types. If the γ^{N_j} follow a decreasing pattern, then an additional different-type firm produces negative spillover effects on firms' payoffs. If the γ^{N_j} follow an increasing pattern, it indicates that an additional different-type firm produces positive spillovers to the other type. The results will be used as a starting point for the estimation of my full two-type model.

Estimation: To simultaneously estimate this augmented ordered probit model with revenue function by maximum likelihood, I assumed that η, ξ, and consequently ω are normally distributed. Econometrically, ω and ξ are correlated because ξ is contained in ω. The economic intuition behind is that entry is more likely to occur in markets where demand shocks are expected to be high. This correlation makes it possible that the effect of N on r is based on a spurious correlation. As Schaumans and Verboven (2015) explain in their paper, population size serves as exclusion restriction to identify the causal effect of N on r. Market size (population) affects entry decisions, N, but it does not directly affect per capita revenues. Finally, if a firm decides not to enter, profits are normalized to zero.

Since revenues are observed conditional on entry ($N > 0$), the likelihood contributions vary according to the market configuration. Hence, for markets with $N = 0$,

$$\Pr(N=0) = 1 - \Phi\left(\frac{X\beta + \ln S + \theta^1 + \gamma_j^N}{\sigma_\omega}\right),$$

and for markets with $N > 0$,

$$f(\ln r)\Pr(N|\ln r) = \frac{1}{\sigma_\xi}\phi\left(\frac{\xi}{\sigma_\xi}\right)\left(\Phi\left(\frac{X\beta + \ln S + \theta^N + \gamma^{N_j} - \left(\frac{\sigma_{\omega\xi}}{\sigma_\xi^2}\right)\xi}{\sqrt{\sigma_\omega^2 - \sigma_{\omega\xi}^2/\sigma_\xi^2}}\right) - \Phi\left(\frac{X\beta + \ln S + \theta^{N+1} + \gamma^{N_j} - \left(\frac{\sigma_{\omega\xi}}{\sigma_\xi^2}\right)\xi}{\sqrt{\sigma_\omega^2 - \sigma_{\omega\xi}^2/\sigma_\xi^2}}\right)\right),$$

where $\xi = \ln r - X\beta - \alpha^N - \dfrac{\delta^{N_j}}{N}$. As in several applications of the type-II Tobit Model, the joint density of per capita revenues and number of firms $f(\ln r, N)$ is estimated as the product of (conditional) probabilities, $f(\ln r)\Pr(N|\ln r)$. Under the assumption that variable profits increase proportionally with market size S, I can therefore identify the variance.

2.3.2 Preliminary evidence

Table 3.3 shows the results for the simultaneous one-type entry model and revenue equation, taking as given the number of different-type firms. I organize the discussion of this section as follows. I first present the effects of demographic characteristics on firms' entry decisions and per capita revenues. Next, I discuss how the entry of bars and cafeterias affect each other's profits. To show the effects of entry more clearly, I estimate the competitive measure of entry thresholds per firm (Bresnahan and Reiss (1991a)).

The parameter estimates of the entry equations show that population's age distribution and the percentage of households with children are important factors to explain both cafeterias and bars' entry decisions. More precisely, the percentage of children, relative to the reference group of adults between 25 and 65 years old, negatively affects cafeterias and bars' profitability. Surprisingly, a similar negative effect is found for the percentage of people between 15 and 24 years old. Finally, the percentage of old people has a significant positive effect on bars' profitability, and a positive but not significant effect on cafeterias. Interestingly, the percentage of households with children negatively affects cafeterias' profitability but it positively affects bars' profitability.

Additionally, both services' entry decisions are negatively affected by per capita income. This suggests that high-income markets tend to have fewer cafeterias and bars. The density of houses and commercial activity are not statistically significant, but I consider those variables important to control for heterogeneity in retail activity across markets. Finally, the total number of supermarkets does not seem to affect cafeterias' entry decisions, yet it has a negative small impact on bars.

The estimates from the revenue equations show that all age groups -compared to adults-, and income per capita have a negative and statistically significant effect on cafeterias' per capita revenues. Bars' per capita revenues, on the other hand, are positively affected by the percentage of households with children and elderly. Also, they are negatively affected by the percentage of children, people between 15 and 24 years old, and the number of supermarkets.

Regarding the same-type fixed effects $\hat{\theta}^N$, the estimates are negative and show a decreasing pattern, which is in line with the assumption that entry decisions are strategic substitutes. Moreover, the effects of the same-type entrants on per capita revenues, measured by $\hat{\alpha}^N$, are large and positive, suggesting that there is some market expansion effect from entry. The $\hat{\alpha}^N$ show a decreasing pattern as well.[8]

Finally, Table 3.3 provides the first set of evidence in favor of positive spillovers between different types of amenities ($(\hat{\gamma}^{N_j} - \hat{\gamma}^{N_j-1}) > 0$ and statistically significant). The increasing pattern is in line with firm clustering: cafeterias' decision to be active in a local market is positively affected by the presence of bars, and vice versa. A complication, however, is that establishing this relationship without accounting for unobserved factors that may be driving the decision of entry for both types, may lead to biased results. Those confounding factors could have been erroneously attributed to positive spillovers in this model. In the full two-type model, I explicitly control for unobserved market characteristics and allow them to be correlated.

As for the entry effect on per capita revenues, the estimated fixed effects $\hat{\delta}^{N_j}$ are positive and statistically significant for cafeterias, meaning that there is a positive effect from bars' entry on cafeterias' per capita revenues. The effect for cafeterias' entry on bars' per capita revenues is not statistically different from zero, unless there are more than 5 cafeterias in the market.

[8] The fixed effects of $\hat{\alpha}^N$ account for the endogeneity of the number of firms over revenues.

Table 2.4: One-type entry model with revenue function

Variables	Cafeterias		Bars	
Entry equation				
Income per capita	-0.028***	(0.010)	-0.051***	(0.017)
Density	-0.003	(0.017)	-0.002	(0.034)
Fraction of households with children	-1.459***	(0.466)	2.903***	(0.162)
Fraction of children	-3.095***	(0.948)	-11.521***	(1.181)
Fraction of young	-5.075***	(0.999)	-3.250***	(0.258)
Fraction of old	0.033	(0.182)	3.528***	(0.229)
Total retail locations	0.049	(0.035)	-0.039	(0.061)
N. supermarkets	0.002	(0.018)	-0.162***	(0.032)
θ^1 $(N = 1)$	-5.523***	(0.259)	-4.580***	(0.229)
θ^2	-6.377***	(0.256)	-5.803***	(0.237)
θ^3	-6.962***	(0.264)	-6.731***	(0.217)
θ^4	-7.377***	(0.294)	-7.540***	(0.240)
θ^5	-7.701***	(0.313)	-8.121***	(0.293)
γ^1 $(N_j = 1)$	0.212	(0.151)	0.222	(0.116)
γ^2	0.332***	(0.117)	0.428***	(0.104)
γ^3	0.460***	(0.129)	0.552***	(0.148)
γ^4	0.501***	(0.138)	1.128***	(0.166)
γ^5	0.847***	(0.155)	1.688***	(0.251)
Revenue equation				
Income per capita	-0.020*	(0.010)	0.001	(0.009)
Density	-0.011	(0.012)	-0.005	(0.024)
Fraction of households with children	-0.198	(0.189)	2.820***	(0.234)
Fraction of children	-2.831***	(0.774)	-3.909***	(0.296)
Fraction of young	-1.404***	(0.342)	-0.634***	(0.098)
Fraction of old	-0.083	(0.161)	4.324***	(0.393)
Total retail locations	-0.024	(0.044)	-0.028	(0.036)
N. supermarkets	0.013	(0.016)	-0.069***	(0.025)
α^1 $(N = 1)$	4.640***	(0.359)	3.005***	(0.187)
α^2	4.477***	(0.306)	2.802***	(0.165)
α^3	4.353***	(0.288)	2.595***	(0.160)
α^4	4.124***	(0.310)	2.384***	(0.161)
α^5	3.811***	(0.307)	1.851***	(0.178)
δ^1 $(N_j = 1)$	0.320*	(0.181)	0.024	(0.065)
δ^2	0.419***	(0.168)	-0.086	(0.130)
δ^3	0.476***	(0.154)	-0.025	(0.169)
δ^4	0.808***	(0.167)	0.020	(0.199)
δ^5	0.852***	(0.182)	0.459**	(0.207)
Covariance matrix				
σ_ω	0.863***	(0.057)	1.575***	(0.075)
σ_ξ	0.792***	(0.041)	0.942***	(0.037)
$\sigma_{\omega\xi}$	-0.390***	(0.075)	-1.010***	(0.054)
N		1,005		1,005
Log likelihood		-2,022.9		-2,462.3

Note: The parameter estimates are based on maximum likelihood estimation of the simultaneous one-type model with revenue equations for each type of service. The different-type entry decision is treated as exogenous variable. Standard errors are in parentheses. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Entry thresholds per firm: To provide further insights into the estimated magnitude of spillover effects, and to produce a benchmark for the full model, I compute the entry thresholds per firm based on the parameter estimates, $S(\hat{N})/N$. Entry thresholds, $S(N)$, are defined as the critical market sizes (population) required to profitably support a certain number of cafeterias (bars), for a given number of bars (cafeterias). Using equation (2.4) for a representative average market ($\omega = 0$ and $X = \bar{X}$), the entry threshold to support N, given N_j is defined by

$$\hat{S}(N) = \exp(-\bar{X}\hat{\beta} - \hat{\theta}^N - \hat{\gamma}^{N_j}). \tag{2.5}$$

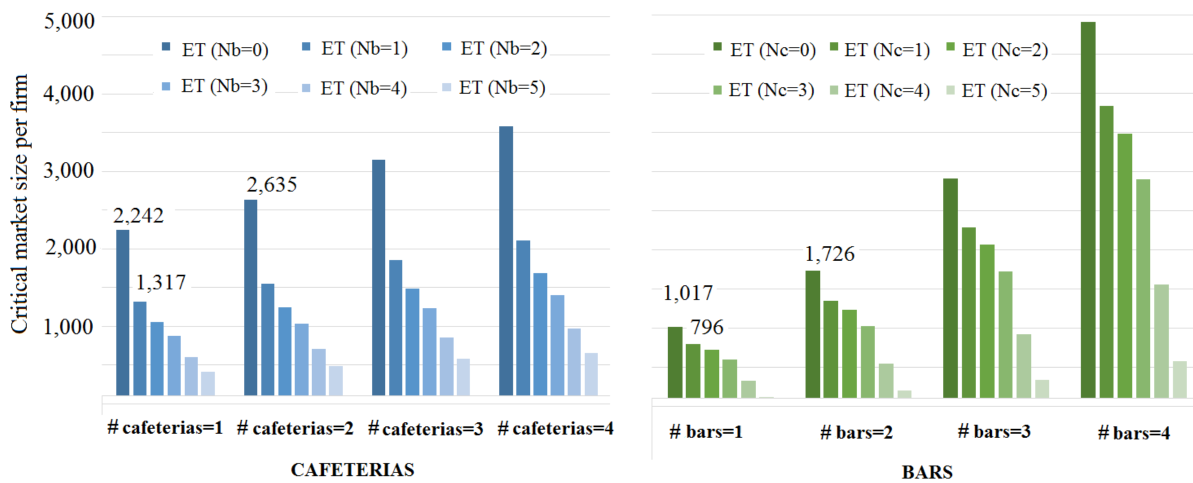
Changes in entry thresholds per firm $\hat{S}(N)/N$ produced by the entry of the same-type firms are typically used as measures of competition. The intuition behind is that a disproportional increase in population to support an additional entrant indicates that entry intensifies competition. Figure 2.1 illustrates how entry thresholds per firm vary under different market configurations. For expository purposes, I present in detail a few cases here, but all estimated entry thresholds per firm can be found in Appendix D (Table 2.7).

First consider the case for cafeterias (left part of the figure). The critical market size needed to support one cafeteria when any bar is around ($N_C = 1, N_B = 0$) is 2,242 people. If an additional cafeteria enters the market such that there are only two cafeterias ($N_C = 2, N_B = 0$), the entry threshold per cafeteria increases to 2,635 people. This disproportionate increasing pattern continues and the magnitude comes from the estimated values of the same-type fixed effects ($\hat{\theta}^N$): a negative impact on payoffs are translated into more people needed to support a firm when there is an additional entrant in the market.

Figure 2.1 also provides information on the positive spillover effects generated by the entry of an additional firm of the other type. As mentioned above, 2,242 people are needed when no bar is present. This amount decreases to a level of 1,317 when the first bar enters ($N_C = 1, N_B = 1$). The decreasing pattern in entry thresholds, for a given number of cafeterias, produced by the entry of additional bars suggest that entry decisions of different type are strategic complements. The presence of a bar increases cafeterias' profitability and the magnitude is based on the values of the estimated $\hat{\delta}^{N_j}$.

In a similar fashion, changes in entry thresholds per firm for bars (right part of the figure) show that bars' competition increases when another bar enters the market. Interestingly, in relation to cafeterias, less people are needed to support a bar, but the same-type fixed entry effect is bigger in relation to the one for cafeterias. About the spillovers generated by cafeterias, the changes in entry thresholds also suggest there is a positive spillover effect generated by

Figure 2.1: Preliminary evidence on spillover effects



Note: Estimated entry thresholds per firm (see Equation 2.5) using parameter estimates from the one-type entry model with revenue equation. Entry thresholds are defined as the minimum amount of people per firm required to support a certain number of cafeterias (bars) in the market, for a given number of bars (cafeterias). The length of each bin indicates this amount.

cafeterias' entry.

Once again, these results should be taken with caution. Extending the model for two types is needed to overcome endogeneity problems. The two-type model directly accounts for unobserved market factors that might generate biases in the spillover effects.

2.4 Incorporating spillover effects

In this section, I present the full two-type entry model with revenue equations. The model extends previous work (Schaumans and Verboven (2015), Ferrari et al. (2010)) by modelling the entry decisions of both types of services allowing for the estimation of spillover effects of entry between different amenity services.

2.4.1 Setup

Firms' entry decisions are modeled as a sequential-move entry game under complete information. Formally, consider a game in which potential firms choose whether to enter or not in a given market. Each firm can be of two types $i = C, B$, where C denotes cafeterias, and B is used for bars. This study assumes that types are previously determined, implying that firms have already decided which type of service they wish to provide.[9] This is a plausible assumption considering that the provision of each service requires specific municipal licenses,[10] and the infrastructure needs to be defined beforehand.

Therefore, the only decision for a firm to make is whether actually enter the market or not. The degree of business/product differentiation (either vertical or horizontal) that a market achieves thus depends on the entry decisions of both types of firms (N_C, N_B). I assume there is free entry and each firm decides to enter only if it is profitable. If a firm decides not to enter, its payoffs are normalized to zero. Profits for each type i in a local market are defined by

$$\Pi_i(N_C, N_B) = \mu_i(N_C, N_B)\, r_i(N_C, N_B)\, S - f_i \tag{2.6}$$

where the variable profits per capita, as before, are disentangled into a percentage markup, $\mu_i(N_C, N_B)$, and a revenue component, $r_i(N_C, N_B)$, both depending on the number of cafeterias and bars. For now, I define profits as the sum of a deterministic component π_i, and a random variable ω_i, which represents the components of firm profits that are unobserved to the econometrician.[11] Then,

$$\Pi_i(N_C, N_B) = \pi_i(N_C, N_B) - \omega_i$$

The relationship within and between types of firms is reflected on how the number of firms of each type affects entry decisions. Similarly to the one-type model presented before, I first assume that entry decisions by firms of the same type are strategic substitutes (Assumption 1). This means that a cafeteria's profitability decreases when another cafeteria enters the market. Likewise, a bar's payoffs decreases when another bar enters.

Assumption 1: *Entry decisions by firms of the same type are strategic substitutes*

$$\begin{aligned} \pi_C(N_C+1, N_B) &< \pi_C(N_C, N_B) \\ \pi_B(N_C, N_B+1) &< \pi_B(N_C, N_B) \end{aligned} \tag{2.7}$$

Besides the same-type entry effect, I make additional assumptions about the strategic interaction between different services. Based on the preliminary evidence showed in the previous section, and following the framework presented by Schaumans and Verboven (2008), I assume

[9] See Mazzeo (2002) and Greenstein and Mazzeo (2006) for cases in which types are endogenous. Their models are based on a Stackelberg entry model in which the most profitable type is chosen.

[10] Bars, for instance, need licenses to sell alcohol.

[11] The exact specification will be explained in subsection 2.4.3.

that entry decisions made by bars and cafeterias are (weak) strategic complements (Assumption 2). In other words, a cafeteria (bar)'s marginal profits from entering are either increasing in or independent of the number of bars (cafeterias).

Assumption 2: *Entry decisions by firms of different type are strategic complements or independent*

$$\begin{aligned} \pi_C(N_C, N_B) &\leq \pi_C(N_C, N_B + 1) \\ \pi_B(N_C, N_B) &\leq \pi_B(N_C + 1, N_B) \end{aligned} \tag{2.8}$$

Assumption 2 allows for positive spillover effects of entry between types. There exist positive spillovers when Assumption 2 holds with strict inequality. Positive spillovers can be explained by either demand or supply-side factors. On the demand side, having more firms in the market may attract more people creating thus a market expansion effect. On the supply side, the presence of bars, for example, may reduce the cafeterias' fixed costs (e.g. advertising costs). I have also considered a model in which entry decisions of different types are strategic substitutes but the data do not support this assumption.[12]

Additionally, in line with previous works (Bresnahan and Reiss (1991a), Mazzeo (2002), Greenstein and Mazzeo (2006)), I assume that the effect of entry of an other-type firm is lower than the effect of entry of a same-type firm (Assumption 3). Hence, a firm' profitability decreases when there is an additional firm of both types in the market.

Assumption 3: *Entry decisions by firms of the same type have a greater impact than different-type firms*

$$\begin{aligned} \pi_C(N_C + 1, N_B + 1) &< \pi_C(N_C, N_B) \\ \pi_B(N_C + 1, N_B + 1) &< \pi_B(N_C, N_B) \end{aligned} \tag{2.9}$$

Based on Assumptions 1, 2 and 3, I can now define the equilibrium number of firms and the implied likelihood function. Although I closely follow the entry game presented by Schaumans and Verboven (2008), my likelihood function differs from theirs due to the inclusion of revenue equations. This imposes additional challenges in the estimation, as shown in more detail in Section 2.4.4.

2.4.2 Equilibrium

As previously mentioned, each type of firm enter if this generates positive profits. Therefore, under free entry, the market configuration ($N_C = n_C, N_B = n_B$) is a Nash equilibrium if and only

[12]The estimated parameters are not consistent with this assumption.

if the random component $\omega = (\omega_C, \omega_B)$ satisfies the following conditions:

$$\begin{aligned} \pi_C(n_C+1, n_B) < \omega_C \leq \pi_C(n_C, n_B) \\ \pi_B(n_C, n_B+1) < \omega_B \leq \pi_B(n_C, n_B). \end{aligned} \tag{2.10}$$

When these conditions are satisfied, it is profitable for n_C cafeterias and n_B bars to enter ($\Pi_i(n_C, n_B) \geq 0$), but any additional bar or cafeteria will not have an incentive to do so. Assumption 1 guarantees that there are realizations of ω for which (2.10) holds, so that the market configuration (n_C, n_B) is observed with positive probability.

Equivalently, replacing the profit equations (2.6) in (2.10) and taking logs,

$$\begin{aligned} \ln \tfrac{\mu_C(n_C+1,n_B)}{f_C} + \ln r_C(n_C+1, n_B) + \ln S < 0 < \ln \tfrac{\mu_C(n_C,n_B)}{f_C} + \ln r_C(n_C, n_B) + \ln S \\ \ln \tfrac{\mu_B(n_C,n_B+1)}{f_B} + \ln r_B(n_C, n_B+1) + \ln S < 0 < \ln \tfrac{\mu_B(n_C,n_B)}{f_B} + \ln r_B(n_C, n_B) + \ln S. \end{aligned} \tag{2.11}$$

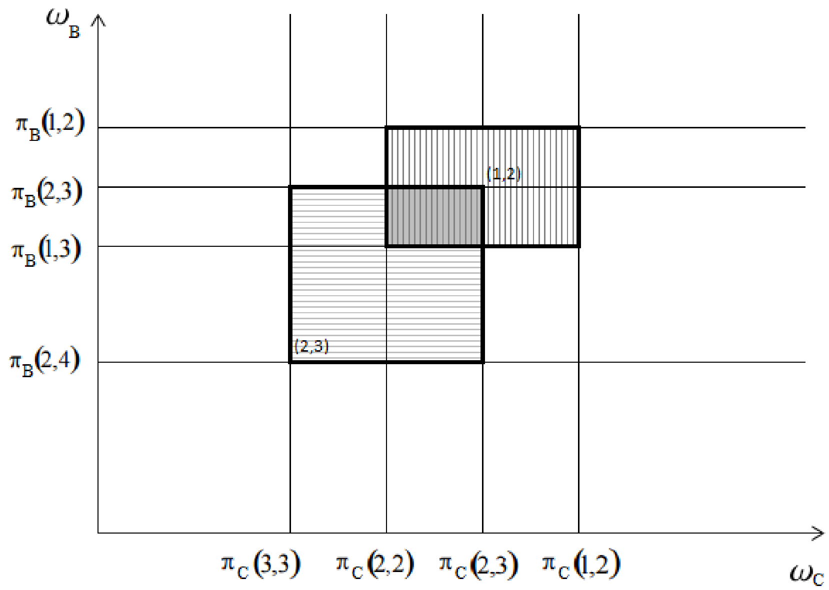
Once I specify each element, these entry conditions, together with the revenue equations, will define my likelihood function. However, the estimation is not straightforward. As it is well known, (n_C, n_B) may show multiplicity with other Nash equilibrium outcomes for some realizations of ω. For example, for some realizations of ω, the market configurations (1,2) and (2,3) are both Nash equilibrium outcomes (see Figure 2.2). The multiplicity arises from coordination problems and the overlapping area in which both markets configurations are Nash equilibria depends on the extent of spillover effects (strategic complementarity). Assumption 3 guarantees that a full overlap does not happen since it states that $\pi_C(2,3) < \pi_C(1,2)$ and $\pi_B(2,3) < \pi_B(1,2)$. In other words, Assumption 3 prevents that the area of ω for which (1,2) is a Nash equilibrium outcome be a subset of the area for which (2,3) is a Nash equilibrium. This ensures that each market configuration is observed with positive probability. Furthermore, the area of multiplicity disappears if firms are independent, i.e. $\pi_C(2,2) = \pi_C(2,3)$ and $\pi_B(1,3) = \pi_B(2,3)$.

In general, the multiplicity of Nash equilibrium outcomes can be characterized as follows.[13] If firms of different types are independent, that is Assumption 2 holds with equality, then the market configuration (n_C, n_B) is the unique Nash equilibrium in the area of ω satisfying (2.11). In contrast, if the entry decisions of different types of firms generate positive spillovers between each other, that is Assumption 2 holds with strict inequality, then for some realizations of ω, (n_C, n_B) may show multiplicity with other Nash equilibrium outcomes:

- (n_C, n_B) may only show multiplicity with Nash equilibrium outcomes of the form $(n_C +$

[13] I refer to the Appendix in Schaumans and Verboven (2008) for the complete derivation.

Figure 2.2: Nash equilibria with strategic complements



Note: This figure illustrates the multiplicity problem. Specifically, it shows how the areas of ω for which the market configurations (1,2) and (2,3) are Nash equilibrium outcomes overlap for some realizations due to the existence of complementarity. *Source:* Schaumans and Verboven (2008).

$m, n_B + m$), where m is a positive or negative integer. Following the same example, if (1,2) is a Nash equilibrium outcome, then there may be multiplicity with (0,1) or (2,3), but not with (2,4).

- (n_C, n_B) necessarily show multiplicity with $(n_C + 1, n_B + 1)$ and $(n_C - 1, n_B - 1)$.
- Whereas (n_C, n_B) may also show multiplicity with $(n_C + m, n_B + m)$ for $m > 1$ or $m < 1$, these areas of multiplicity are necessarily a subset of the areas of multiplicity with $(n_C + 1, n_B + 1)$ and $(n_C - 1, n_B - 1)$

Together, these three claims imply that the area of ω for which (n_C, n_B) shows multiplicity with any other Nash equilibrium outcome is simply given by the areas of overlap with $(n_C + 1, n_B + 1)$ (given by (2.12)) and $(n_C - 1, n_B - 1)$. The area of multiplicity with $(n_C + 1, n_B + 1)$

is given by

$$\begin{aligned}\pi_C(n_C+1,n_B) &< \omega_C \leq \pi_C(n_C+1,n_B+1)\\ \pi_B(n_C,n_B+1) &< \omega_B \leq \pi_B(n_C+1,n_B+1)\end{aligned} \tag{2.12}$$

and similarly for (n_C-1,n_B-1).

In line with Mazzeo (2002) and to obtain unique predictions, I add additional structure to the entry game and assume firms make their entry decision in a sequential order. This means that each firm observes all previous entry decisions. I then refine the Nash equilibrium concept to that of subgame perfection. When entry decisions of different types of firms are strategic complements, it is not necessary to make specific assumptions about the exact ordering of entry moves, as it is when entry decisions are strategic substitutes.[14] When there are multiple Nash equilibrium outcomes, the unique subgame perfect equilibrium is the one with the largest number of firms. The ones with a fewer number of firms cannot be subgame perfect because any firm will then have an incentive to enter in anticipation of triggering entry of the other type in the future. Considering the example of Figure 2.2, the market configuration (2,3) would then be selected as the subgame perfect equilibrium when there is multiplicity with (1,2). Therefore, (n_C+1,n_B+1) will be a subgame perfect Nash equilibrium if and only if (i) ω satisfies conditions (2.11) and (ii) ω does not satisfy conditions (2.12). Assuming that ω follows certain distribution, it is possible to derive the likelihood function.

2.4.3 Econometric specification

I use the same econometric specification as in the one-type model. The main difference is that the number of different-type firms, N_j, is not taken as given, but it is rather the result of the entry game. Accordingly, per capita revenues of type i depend on observed market characteristics X, the number of same-type competitors N_i, as well as on the number of different-type firms N_j. The effects of entry are also measured by the fixed effects $\alpha_i^{N_i}$ and $\delta_i^{N_j}$, which measure the effects of each additional same-type and different type entrant, respectively. Also, the fixed effects related to firms of different types are divided by the number of market participants, N_i. The same intuition explained in Section 2.3 applies. Finally, per capita revenues depend on unobserved market-specific revenue shocks, ξ_i. Then,

$$\ln r_i(N_i,N_j) = X\lambda_i + \alpha_i^{N_i} + \frac{\delta_i^{N_j}}{N_i} + \xi_i. \tag{2.13}$$

[14] See Cleeren et al. (2010) for an application where entry decisions of different types are strategic substitutes.

Concerning the ratio of markups over fixed costs per type, I specify it as a function of observed market characteristics X, the number of both types of firms using fixed effects, $\tau_i^{N_i}$ and $\rho_i^{N_j}$, and an unobserved market-specific error term η_i

$$\ln \frac{\mu_i(N_i,N_j)}{f_i} = X\varphi_i + \tau_i^{N_i} + \rho_i^{N_j} - \eta_i \tag{2.14}$$

Substituting (2.13) and (2.14) in (2.11), the entry conditions can be expressed as

$$X\beta_i + \ln S + \theta_i^{N_i+1} + \gamma_i^{N_j} < \omega_i < X\beta_i + \ln S + \theta_i^{N_i} + \gamma_i^{N_j}, \tag{2.15}$$

where I define

$$\begin{aligned}
\beta_i &\equiv \lambda_i + \varphi_i, \\
\theta_i^{N_i} &\equiv \alpha_i^{N_i} + \tau_i^{N_i}, \\
\gamma_i^{N_j} &\equiv \frac{\delta_i^{N_j}}{N_i} + \rho_i^{N_j}, \\
\omega_i &\equiv \eta_i - \xi_i.
\end{aligned}$$

The key parameters in the model are the strategic effects of entry, captured by $\theta_i^{N_i+1}$ and $\gamma_i^{N_j}$. In particular, positive spillovers exist if the $\gamma_i^{N_j}$ are statistically larger than zero, and show an increasing pattern meaning that each additional entrant favors the other service's profitability.

To estimate this model, there are three cases of interest depending on the market configuration. The likelihood contribution differs for each case (more details are presented in Appendix A).

1. For markets without cafeterias and bars, i.e. $(N_C = 0, N_B = 0)$, the per capita revenues and Nash equilibrium conditions are:

   - (r_C, r_B) unobserved

   - $$\begin{aligned} X\beta_C + \ln S + \theta_C^1 &< \omega_C \\ X\beta_B + \ln S + \theta_B^1 &< \omega_B \end{aligned}$$

2. For markets where one of the services is not provided, two possibilities arise: there are only cafeterias $(N_C > 0, N_B = 0)$ or only bars $(N_C = 0, N_B > 0)$ in the market. To illustrate, when $(N_C = 0, N_B > 0)$, the per capita revenues and Nash equilibrium conditions are:

- r_C unobserved

  $\ln r_B = X\lambda_B + \alpha_B^{N_B} + \xi_B$

- $X\beta_C + \ln S + \theta_C^1 + \gamma_C^{N_B} \quad < \omega_C$

  $X\beta_B + \ln S + \theta_B^{N_B+1} \qquad < \omega_B < X\beta_B + \ln S + \theta_B^{N_B}$

3. For markets with cafeterias and bars ($N_C > 0, N_B > 0$), the per capita revenues and Nash equilibrium conditions are:

   - $\ln r_C = X\lambda_C + \alpha_C^{N_C} + \frac{\delta_C^{N_B}}{N_C} + \xi_C$

     $\ln r_B = X\lambda_B + \alpha_B^{N_B} + \frac{\delta_B^{N_C}}{N_B} + \xi_B$

   - $X\beta_C + \ln S + \theta_C^{N_C+1} + \gamma_C^{N_B} < \omega_C < X\beta_C + \ln S + \theta_C^{N_C} + \gamma_C^{N_B}$

     $X\beta_B + \ln S + \theta_B^{N_B+1} + \gamma_B^{N_C} < \omega_B < X\beta_B + \ln S + \theta_B^{N_B} + \gamma_B^{N_C}$

Before proceeding with the estimation, I describe the key assumptions I use to identify the model. First, conditional on observed market characteristics, the number of cafeterias and bars may be correlated because of positive spillovers of entry or because of unobserved market characteristics affecting both services. The latter is captured by the correlation parameters in the covariance matrix. Given that I do not have information that allows me to non-parametrically identify both effects, I rely on parametric assumptions and assume that ω follows a particular distribution. Once I do that, I can disentangle both effects.

Second, in this model, as in the one-type model, population serve as exclusion restriction to identify the effect of (N_i, N_j) on (r_i, r_j). In addition, to identify the first same-type fixed effect α_i^1, I normalize the constant term to zero ($\beta_i^0 = 0$). However, not all the fixed effects are estimated. I assume that the first different-type fixed effect is equal to zero, i.e. $\gamma_i^0 = 0$. Therefore, as mentioned earlier, there exists positive spillover effects if the $\gamma_i^{N_j}$ are positive and increasing. Finally, similar to the one-type case, I identify the scale of payoffs by assuming that the variable profits increases proportional to population.

In the next subsection I proceed with the definition of the likelihood function when revenue equations are included. The estimated parameters will be consistent with the model if they satisfy the conditions from Assumptions 1, 2 and 3.

2.4.4 Estimation

This is a simultaneous entry model with revenue equation extended for two types. Econometrically, the error terms $\omega = (\omega_C, \omega_B)$ and $\xi = (\xi_C, \xi_B)$ are correlated since ξ_i enters $\omega_i = \eta_i - \xi_i$. As in the one-type model, this correlation arises here for economic reasons: firms tend to enter a market under high demand shocks ξ. To estimate the model, I assume that $\varepsilon \equiv (\omega_C, \omega_B, \xi_C, \xi_B)$ follows a tetravariate normal distribution $f(.)$, with zero means and covariance matrix Σ, such that

$$\Sigma = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} & \sigma_{\omega_C\xi_C} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} & \sigma_{\omega_B\xi_C} & \sigma_{\omega_B\xi_B} \\ \sigma_{\omega_C\xi_C} & \sigma_{\omega_B\xi_C} & \sigma^2_{\xi_C} & \sigma_{\xi_C\xi_B} \\ \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} & \sigma_{\xi_C\xi_B} & \sigma^2_{\xi_B} \end{bmatrix}$$

Given the joint density of ε, the probability of observing a market configuration (n_C, n_B) and a corresponding level of revenues (r_C, r_B) as the unique subgame perfect Nash equilibrium can be estimated. For expository reasons, I present the likelihood contribution for the case in which both consumption amenities are available, i.e. $(n_C > 0, n_B > 0)$. The likelihood contribution for the other two cases are presented in Appendix A.

$$\begin{aligned} &f(\ln r_C, \ln r_B, N_C = n_C, N_B = n_B) \\ &\qquad = \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C,n_B)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C,n_B)} f_{\omega_C,\omega_B,\xi_C,\xi_B}(u_C, u_B, \xi_C, \xi_B)\, \mathrm{d}u_C \mathrm{d}u_B \\ &\qquad - \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C+1,n_B+1)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C+1,n_B+1)} f_{\omega_C,\omega_B,\xi_C,\xi_B}(u_C, u_B, \xi_C, \xi_B)\, \mathrm{d}u_C \mathrm{d}u_B \end{aligned}$$

with $\xi_i = \ln r_i - X\lambda_i - \alpha_i^{n_i} - \frac{\delta_i^{n_j}}{n_i}$. I estimate this likelihood as a product of (conditional) bivariate normals $f(\omega_C, \omega_B, \xi_C, \xi_B) = f(\xi_C, \xi_B) \times f\big((\omega_C, \omega_B)|(\xi_C, \xi_B)\big)$. Consequently, the likelihood contribution is redefined as:

$$\begin{aligned} &f(\ln r_C, \ln r_B) P((N_C = n_C, N_B = n_B)|(\ln r_C, \ln r_B)) \\ &\qquad = f(\xi_C, \xi_B) \times \Big(\int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C,n_B)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C,n_B)} f(u_C|(\xi_C, \xi_B), u_B|(\xi_C, \xi_B))\, \mathrm{d}u_C \mathrm{d}u_B \\ &\qquad - \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C+1,n_B+1)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C+1,n_B+1)} f(u_C|(\xi_C, \xi_B), u_B|(\xi_C, \xi_B))\, \mathrm{d}u_C \mathrm{d}u_B \Big) \end{aligned}$$

where $f(\xi_C, \xi_B)$ denotes the bivariate normal distribution of $\xi = (\xi_C, \xi_B)$ with zero mean and covariance:

$$\Sigma_{\xi_C\xi_B} = \begin{bmatrix} \sigma^2_{\xi_C} & \sigma_{\xi_C\xi_B} \\ \sigma_{\xi_C\xi_B} & \sigma^2_{\xi_B} \end{bmatrix},$$

and $f(\omega_C|(\xi_C, \xi_B), \omega_B|(\xi_C, \xi_B))$ denotes the bivariate normal distribution of $\omega = (\omega_C,\, \omega_B)$ given $\xi = (\xi_C, \xi_B)$, with conditional expectation $\mu_{\omega.\xi}$, and conditional covariance $\Sigma_{\omega.\xi}$. To obtain $\mu_{\omega.\xi}$ and $\Sigma_{\omega.\xi}$, I split Σ, such that

$$\Sigma = \begin{bmatrix} \Sigma_{\omega\omega} & \Sigma_{\omega\xi} \\ \Sigma_{\xi\omega} & \Sigma_{\xi\xi} \end{bmatrix}.$$

Then,

$$\mu_{\omega.\xi} = \mu_\omega + \Sigma_{\omega\xi}\Sigma^{-1}_{\xi\xi}(\xi - \mu_\xi)$$

$$\Sigma_{\omega.\xi} = \Sigma_{\omega\omega} - \Sigma_{\omega\xi}\Sigma^{-1}_{\xi\xi}\Sigma_{\xi\omega}$$

Σ is symmetric, therefore $\Sigma_{\xi\omega} = \Sigma_{\omega\xi}$. In Appendix A, I show the exact values of $\mu_{\omega.\xi}$ and $\Sigma_{\omega.\xi}$.

2.5 Results

This section presents the main results of the full-two type entry model with revenue equations. I briefly discuss the impact of the observable market characteristics on both types' entry decisions and revenues. The estimates are very similar to the baseline model, so I only report them in Appendix B. My main interest is in the effects of entry both between and within types, so I discuss them more extensively. To this end, I first report the parameter estimates in Table 2.5. Next, I construct the entry thresholds per firm, and compare them to the ones from the baseline model.

In line with previous results, the population's age distribution has an important effect on entry decisions, particularly for bars. The percentage of children, with respect to the base of adults between 25 and 65 years old, affects negatively bars' entry decisions. This effect is stronger than the one exerted by people between 15 and 24 years old. The percentage of elderly has a significant positive effect on bars' profitability. This might be explained by the fact that retired people have more available time to socialize and bars provide space for this social interaction. This explanation does not apply to cafeterias. Consistently, I find that the percentage of old people, relative to adults, does not have a statistically significant effect on cafeterias' profitability. Finally, the percentage of young people has a negative impact on cafeterias' entry; this effect is stronger compared to the one for bars.

Per capita income, on the other hand, has a very small significant effect on cafeterias' entry exclusively. This confirms the result from the baseline model: markets with low-income per capita tend to have more cafeterias. The effect does not remain relevant to explain bars' entry decisions though. Also, the percentage of households with children affects negatively to cafeterias' but positively to bars' profitability. In addition, the presence of supermarkets affects negatively bars' entry decisions but does not have an impact on cafeterias'.

The estimates from revenue equations show that all age groups, compared to the reference group of adults, have a statistically significant effect on bars' per capita revenues. The signs of these effects are similar to the ones just described: the percentage of children and young population have a negative effect, while the percentage of elderly presents a positive one. For cafeterias, the only age group that significantly affects per capita revenues are children, with a large negative effect.

Lastly, both bars' and cafeterias' revenues are positively affected by the percentage of households with children. Per capita income has a very small but significant effect on cafeterias' per capita revenues. The number of supermarkets does not have any impact on either types' revenues.

The key structural estimates are summarized in Table 2.5. This table presents the estimated fixed effects of entry, as well as, the estimates of the covariance matrix. As previously mentioned, conditional on observed market characteristics, the number of cafeterias and bars may be correlated due to positive spillovers of entry (captured by the $\hat{\gamma}^{N_j}$ and $\hat{\delta}^{N_j}$) or due to unobserved market characteristics affecting both services. The model permits to control for the last factor, and to identify and correctly measure, under parametric assumptions, spillover effects of entry between different types. Precisely, the difference between the estimated fixed effects of the full model and the ones based on the baseline (one-type) model confirms the relevance of my extension to a two-type framework.

Concerning the strategic interaction within same-type firms, the estimates are consistent with the assumption that entry decisions are strategic substitutes. Therefore, the entry of an additional cafeteria reduces cafeterias' profitability. Similar effects are found for bars. This is shown by the decreasing pattern in $\hat{\theta}_i^{N_i}$. A negative difference between $\hat{\theta}_i^{N_i}$ and $\hat{\theta}_i^{N_i-1}$ means that the entry of the Nth-entrant has a negative impact on competitors. The effect of the same-type entry on per capita revenues is also in line with previous results: estimated fixed effects

Table 2.5: Full two-type entry model with revenue equations

Variables	**Cafeterias**		**Bars**	
Entry equation				
θ^1 ($N_i = 1$)	-5.385***	(0.231)	-4.131***	(1.360)
θ^2	-6.369***	(0.229)	-5.240***	(1.331)
θ^3	-7.040***	(0.233)	-6.085***	(1.160)
θ^4	-7.565***	(0.332)	-6.836***	(1.392)
θ^5	-8.080***	(0.333)	-7.405***	(1.380)
γ^1 ($N_j = 1$)	0.413***	(0.098)	2.6E-04	(0.635)
γ^2	0.672***	(0.061)	9.6E-04	(0.630)
γ^3	0.847***	(0.132)	1.0E-03	(0.965)
γ^4	1.111***	(0.314)	0.228	(0.424)
γ^5	1.392***	(0.264)	0.760***	(0.226)
Revenue equation				
α^1 ($N_i = 1$)	4.596***	(0.432)	3.460***	(0.739)
α^2	4.283***	(0.521)	3.179***	(0.799)
α^3	4.137***	(0.728)	2.961***	(0.651)
α^4	3.876***	(0.671)	2.729***	(0.698)
α^5	3.569***	(0.626)	-0.183	(0.224)
δ^1 ($N_j = 1$)	0.009	(0.215)	-0.054	(0.240)
δ^2	0.013	(0.209)	-0.298	(0.346)
δ^3	-0.089	(0.356)	-0.298	(0.799)
δ^4	0.188	(0.474)	-0.553	(0.475)
δ^5	-0.157	(0.126)	2.166***	(0.741)
Covariance matrix				
σ_{ω_C}	1.032***	(0.129)		
σ_{ω_B}	1.462***	(0.080)		
σ_{ξ_C}	0.706***	(0.019)		
σ_{ξ_B}	0.869***	(0.022)		
$\sigma_{\omega_C\omega_B}$	-0.286***	(0.088)		
$\sigma_{\omega_C\xi_C}$	-0.341*	(0.200)		
$\sigma_{\omega_C\xi_B}$	0.059	(0.050)		
$\sigma_{\omega_B\xi_C}$	-0.227**	(0.109)		
$\sigma_{\omega_B\xi_B}$	-0.861***	(0.086)		
$\sigma_{\xi_C\xi_B}$	0.159**	(0.076)		
Control variables				*Yes*
N. observations				1,005
Log likelihood				-4,352.8

Note: This table reports the estimated strategic effects of entry and the parameter estimates of the covariance matrix based on the full two-type entry and revenue model. The parameters are estimated by maximum likelihood. Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

show a positive but decreasing pattern.

Most importantly, concerning the strategic interaction between different types of amenities, Table 2.5 shows that, controlling for observed and unobserved market characteristics, spillover effects of entry between cafeterias and bars are found in one direction. Specifically, bars' entry positively affects cafeterias' profitability, found by the positive and significant values of the $\hat{\gamma}_C^{N_B}$. Their increasing pattern indicates that each additional bar generates positive spillovers on cafeterias. The number of cafeterias, on the other hand, does not have an impact on bars' entry decisions (unless there are five or more). The estimated fixed effects are equal to zero for the first three cafeterias, and for the fourth cafeteria the effect is positive but not significantly different from zero.[15]

Generally, it is not straightforward to interpret these parameters as they capture several effects on variable profits, which includes per capita revenues, percentage markups, and fixed costs. My model enables to provide additional insights. When analyzing the effect on per capita revenues, the estimated effect of bars' entry on cafeterias' per capita revenues ($\hat{\delta}^{N_B}$) is not statistically different from zero. This implies that bars' spillover effects might be mostly related to cafeterias' fixed costs or percentage markups.

A possible explanation for the asymmetric spillover effects might be related to consumers' behavior. People, when going out, primarily search for places that facilitate social interactions. Bars, in contrast to cafeterias, provide the space for people to socialize. Cafeterias can benefit from the foot-traffic generated by the presence of bars. For example, cafeterias can lower their fixed costs, such as advertising. One can think of a cafeteria entering a street where people rarely transit. The firm might need to invest more to inform people about its presence. In contrast, when bars are located nearby, this investment might not be needed.

Another related explanation is that areas with bars (or bars themselves) could be seen by consumers as trendy places. The "hipper" the area (bar) is, the larger the level of margins cafeterias might be able to enjoy. In that respect, the fact that cafeterias do not have a positive effect on bars might be explained by the perception consumers' have on takeaway places. It is less likely that one cafeteria converts an area in a vibrant place to go out. Perhaps a conglomerate of cafeterias attracts more people. That might explain why positive spillover effects exist when 5 or more cafeterias are present in the market.

The literature on spillovers of entry identifies several other mechanisms, but most of them do not seem to be suitable for my study. For example, Toivanen and Waterson (2005) and

[15] Also, the estimated parameters are consistent with the assumptions of the model, such that the entry effect of different types is less strong than the entry effect of the same type of firms.

Yang (2016) identify learning as an important factor to explain agglomeration. The idea is that, besides unobserved heterogeneity and demand spillovers, learning comes into play when retailers face uncertainty about the profitability of the market. An uninformed retailer tends to follow successful rival incumbents into the same markets or avoid entering those in which rival incumbents have failed. Both studies are based on the entry behavior of hamburger chain stores, like McDonalds and Burger King, which offer products that are likely to be more substitutable to one another (Yang (2016)). Learning seems to be more plausible within the same type of service than between different types. If this effect is present, the parameter estimates indicate that the competitive effect within types is stronger.

In addition, the type of bars and cafeterias included in this study are single-establishments, which discards any explanation related to the dynamics of chain stores. In that sense, features such as economies of density are also not applicable here (see Holmes (2011) and Jia (2008)).

Finally, as Datta and Sudhir (2013) note, not correctly accounting for local heterogeneity leads to misspecification errors that might overstate the importance of spillover effects. Therefore, even though the full model controls for both observed and unobserved market characteristics, I present as robustness check the full model estimates when markets defined as city centers are excluded from my sample.[16] As mentioned earlier, consumer demand might be higher in areas with more foot-traffic or higher-quality commercial places. The results are shown in Appendix C and the estimated fixed effects are similar to the ones presented in this section.

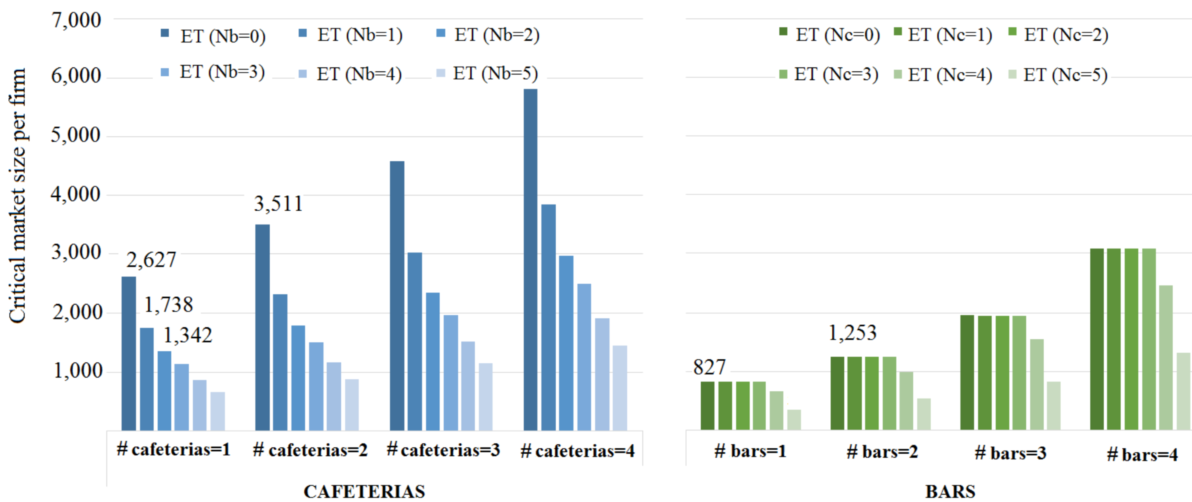
Entry thresholds per firm: In interpreting the full model results, it is worth examining the entry thresholds per firm as well. As I previously explained, entry thresholds are the critical market sizes (population) needed to profitably support a certain number of cafeterias (bars), for a given number of bars (cafeterias). Evaluated at $\omega_i = 0$ and $\bar{X}$, the entry threshold $\hat{S}(N_i)$ to support N_i, given N_j, is defined by

$$\hat{S}(N_i) = \exp(-\bar{X}\hat{\beta} - \hat{\theta}^{N_i} - \hat{\gamma}^{N_j}). \tag{2.16}$$

Changes in entry thresholds per firm $\hat{S}(N_i)/N_i$ are typically used as a measure of competition. A disproportional increase in population to support an additional entrant indicates that

[16] I use data from ABF Research Company to perform this robustness check. The data classify postal code areas in 5 types: city center, just outside city center, outside city limits, center village and suburb. This classification is based on population density, density of houses, type of houses and commercial activity, among other demographic characteristics. I convert the data to my market definition and exclude those markets defined as city center from my sample. After this exclusion my sample contains 989 local markets.

Figure 2.3: Spillover effects



Note: Estimated entry thresholds (see Equation 2.16) using parameter estimates from the two-type entry model with revenue equations. Entry thresholds are defined as the minimum amount of people per firm required to support a certain number of cafeterias (bars) in the market, for a given number of bars (cafeterias).

entry intensifies competition. Figure 2.3 illustrates how entry thresholds per firm vary under different market configurations.[17]

Following the structure presented in section 2.3.2, first consider cafeterias' entry thresholds (left part of the figure). The estimated critical market size needed to support one cafeteria, given zero bars around ($N_C = 1, N_B = 0$), is 2,627 people. If an additional cafeteria enters the market, such that ($N_C = 2, N_B = 0$), the entry threshold per cafeteria increases to 3,511 people. The estimated values of the same-type fixed effects ($\hat{\theta}^{N_C}$) shapes the increasing pattern of the entry thresholds per firm. Entry produces a negative impact on profits, therefore, more people are needed to support the installed competitors.

A similar pattern is found for bars (right part) when the same type of competitors enter the market: 827 people are needed to support one bar when no cafeterias are around, but the number increases to 1,253 when an additional bar enters. As in the baseline model, in relation to cafeterias, less people are needed to support a bar, but the same-type effect seems to be stronger for bars (an increase of 51% compared to 34% for cafeterias).

Figure 2.3 clearly shows how positive spillover effects play a role for cafeterias (from bars'

[17] All estimated entry thresholds per firm can be found in Appendix D (Table 2.8).

entry), but not vice versa. On the one hand, the number of people needed to support one cafeteria substantially decreases when the first bar enters (from a level of 2,627 to a level of 1,738). In line with preliminary findings, the results show that the most important spillover effect of entry is produced when the first bar enters the market. A decreasing pattern in entry thresholds continues but the additional positive effect slightly decreases in magnitude when subsequent bars enter. These changes are based on the values of the estimated fixed effect $\hat{\delta}^{N_j}$.

On the other hand, concerning the spillovers generated by cafeterias, the graph illustrates the main changes with respect to the baseline model. Bars' entry thresholds are unaffected when cafeterias enter the market, at least for the first four entrants.[18] The fifth entrant has a significant positive effect.

In summary, the results confirm the importance of incorporating a second type into the baseline model. Modelling the entry decision of both types permits a more precise estimation of spillover effects. I find that spillovers mainly go in one direction. The policy implications of accounting for such effects are relevant, as I show in the next section. Mistakenly assuming that spillovers are symmetric (or that they do not exist) may lead to the design of less effective urban policies. This is particularly relevant for less attractive areas with fewer firms in the market.

2.6 Policy experiments

I perform two policy experiments. First, I assess how providing a tax relief to either cafeterias or bars, under the presence of spillover effects, affects the whole market structure. The results show the importance of designing incentive programs that take into consideration entry spillovers' magnitude. Second, provided that policymakers need resources to support these programs, I analyze the convenience of two different redistribution schemes (across and within cities) to increase the provision of amenities, especially in less attractive areas. In both cases, I evaluate results by analyzing the changes on the number of businesses and geographic coverage.

2.6.1 Targeting a tax relief in the presence of spillover effects

Cities have traditionally tried to attract businesses by offering them tax breaks and other cash incentives.[19] At a time in which municipal budgets are increasingly strained, new tools that

[18] The estimate for the fourth entrant is positive but not statistically different from zero.

[19] Non-monetary incentives are also effective in attracting new firms. According to an article published by The Economist (2014), small businesses judge cities' "business climate" not only based on tax rates, but also on how costly it is for them to comply with municipal regulations. Since non-monetary incentives are ultimately reflected

allow policymakers to evaluate and understand the costs and benefits of incentive programs are needed. This section shows how spillovers play a key role in this respect.

In my experiment, I assume that local governments provide a tax relief to either bars or cafeterias such that they perceive a 25% increase in their revenues. In other words, per capita revenues are adjusted upward by a factor Δ, where $\Delta = 1.25$. I use the estimated parameters of the full model to make new entry predictions under these two scenarios: $\Delta_C = 1.25$ and $\Delta_B = 1.25$. For $\Delta = 1$, I obtain the predictions when no policy is implemented, which serves as a benchmark for both incentive schemes. Following Schaumans and Verboven (2008), I define the level of profits such that $\Pi_i^*(N_i, N_j) = \mu(N_i, N_j)\, r(N_i, N_j)\, S \exp(-\omega_i) - f_i$. This form is based on Genesove (2001) and it assumes that the error term enters in a multiplicative manner (rather than additive as in Bresnahan and Reiss (1991a)). Given this, a change in per capita revenues from r to Δr enters the profit equation in the following manner:

$$\Pi_i^*(N_i, N_j) = \mu(N_i, N_j)\, \Delta r(N_i, N_j)\, S \exp(-\omega_i) - f_i.$$

Firms enter if and only if $\Pi_i^*(N_i, N_j) > 0$. Equivalently,

$$\ln \frac{\mu_i(N_i, N_j)}{f_i} + \ln r_i(N_i, N_j) + \ln(\Delta) + \ln S - \omega_i > 0 \tag{2.17}$$

I make new entry predictions by replacing (2.13) and (2.14) into (2.17) and replacing the corresponding estimates from the full model. Specifically, I take 1,000 draws from the estimated tetraviarate normal distribution for the error terms $\varepsilon = (\omega_C, \omega_B, \xi_C, \xi_B)$ for each market. Then, per market and draw, I compute the maximum number of cafeterias and bars that can profitably enter. With this, I compute the probabilities of observing different market configurations (N_C, N_B). I then average these probabilities over all draws. I finally calculate the average number of firms per market by multiplying this average probability by the number of markets.

Findings: Figure 2.4 summarizes the main results. As previously mentioned, I use two types of indicators to assess the effectiveness of both incentive schemes: geographic coverage and the number of businesses. If policy makers would like to increase amenities in less attractive areas, then geographic coverage may be of special interest to them. As one could expect, geographic coverage would generally increase when revenues are upward scaled. In particular, when tax reliefs are given to cafeterias, the coverage of this service increases such that 15%

in variable profits, the analysis of this section more generally applies to these types of incentives.

of the markets that did not have any cafeterias, they now have at least one cafeteria. Similarly, if bars receive this tax relief, 17% of the markets without any bars, they have at least one bar after the policy. Additionally, the results show that when monetary incentives are targeted to bars, given their positive effect on cafeterias' profits, 4% of the markets without cafeterias have now at least one cafeteria in the market. On the contrary, when giving incentives to cafeterias, only 1% of the markets that did not have any bars, now have at least one bar. This explains why, at aggregated level, providing monetary incentives to promote bars' entry increases the coverage of services by 17%, which constitutes a greater effect compared to the one induced by cafeterias (11%). This difference reflects the asymmetric spillover effects cafeterias and bars have between each other.

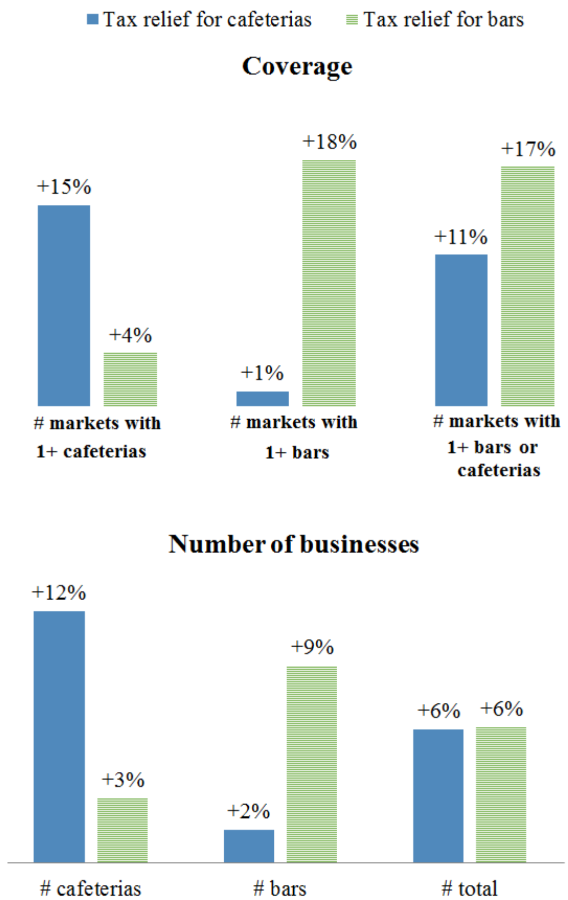
Regarding the total number of businesses, a more careful analysis needs to be done. The number of cafeterias, as well as of bars, is predicted to increase when revenues are scaled up by 25%: a total of 234 new cafeterias and 215 new bars enter the market. This represents an increase of 12% for cafeterias and 9% for bars over their previous level. A policy maker who only measures effectiveness of policies in terms of the total number of new businesses, abstracting from spillover effects, could erroneously conclude that providing incentives to cafeterias is more effective in attracting new businesses into the market. However, it can be observed that, when considering spillover effects, increasing bars' revenues has an indirect effect on cafeterias' entry decisions: 60 more cafeterias enter the market, which constitutes an increase of 3%. This effect is higher than cafeterias' spillover effect on bars (36 new bars, a 2% over its original level). If, additionally, policy makers value variety of services, focusing policies on bars can be more beneficial.

When cafeterias receive a tax relief, the entry of 36 new bars may seem to contradict my previous finding that spillover effects are mainly operating in one direction: from bars entry to cafeterias' profits. Nevertheless, these additional new bars stem from the fact that the fourth and fifth cafeteria have a positive effect on bars' entry. Given that it is more probable to find 4 or 5 cafeterias in more populate markets, Figure 2.5 shows the results when I divide the sample in two in terms of population size: small (below the median) and big (above the median).[20]

As the left part of Figure 2.5 shows, the spillovers of bars' entry over cafeterias predominate in small markets. Policies targeted to bars increases cafeterias coverage (+3%), as well as the number of businesses (+5%). These effects are larger than the one from cafeterias' on bars: geographic coverage remain unchanged, and the number of bars increases only in 1%. Another way to look at this is through the new businesses created in small markets. From the total

[20]The median population size of my total sample is 3,800 inhabitants.

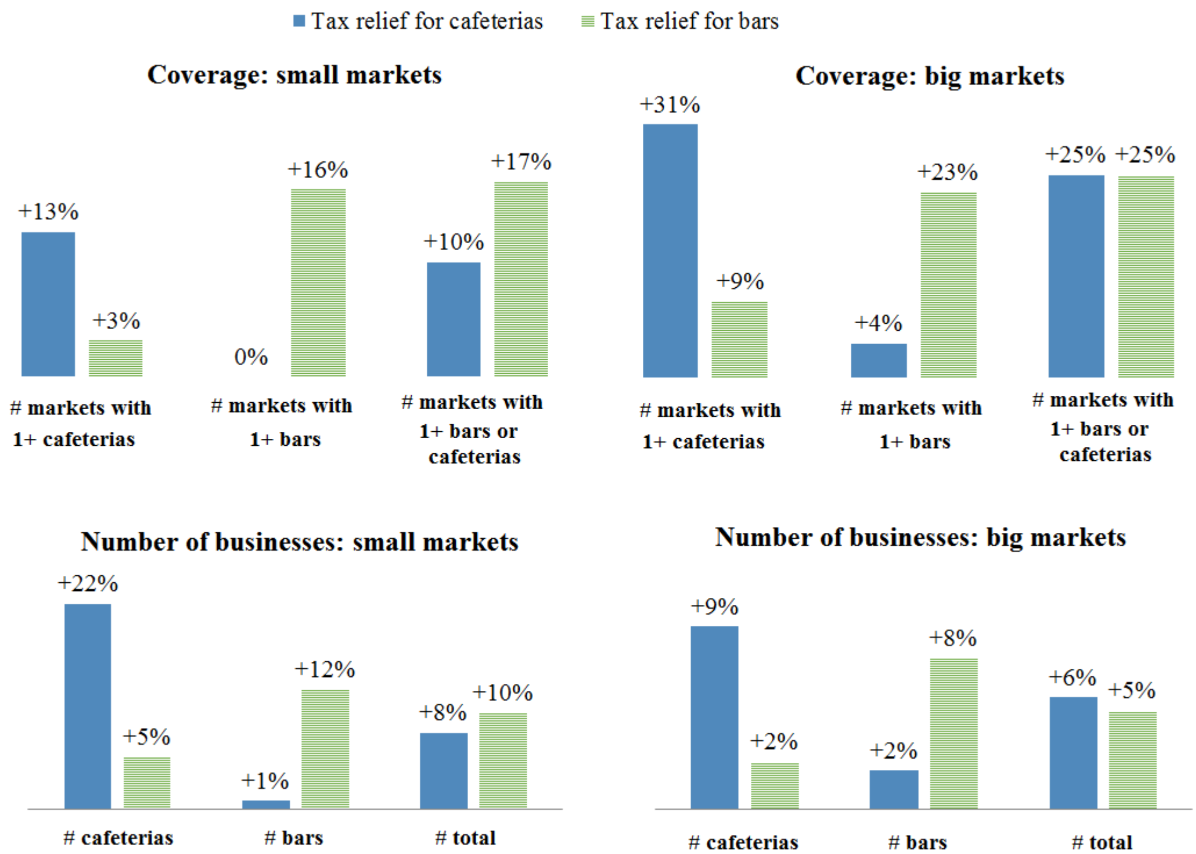
Figure 2.4: Effects of alternative tax relief schemes



Note: This figure compares the changes in coverage and number of businesses when tax reliefs are given to either cafeterias or bars, such that their revenues are scaled up by 25%. The results are based on entry predictions performed with the estimates of the full model.

businesses created from bars' entry, 19% are cafeterias. While from the total businesses created from cafeterias' entry, 7% are bars. In big markets, this difference is less pronounced: both types' entry generates an increase of around 2% in the number of businesses of the other type. These results demonstrate the importance of spillover effects for city planners. If the objective is to increase amenities in less attractive markets, targeting incentives toward amenities that create the largest spillover effects is more effective. My next policy experiment illustrates how spillovers play a role at city level. I further explore how policymakers can make a city more attractive by using nonuniform tax schemes.

Figure 2.5: Effects of alternative tax relief schemes on big and small cities



Note: This figure summarizes the changes in coverage and number of businesses for small and big markets (markets within my sample with population below and above the median, respectively) when monetary incentives (25% tax reliefs) are given to either cafeterias or bars. The results are based on entry predictions performed with the estimates of the full model.

2.6.2 Making small cities more attractive through redistributive policies

Over the last decade, domestic migration towards big cities has become more pronounced in the Netherlands (PBL (2013)). If the offer of amenities decreases in response to this migration, it can eventually be detrimental for less mobile population living in small cities, such as elderly and poorer people. In times of fiscal constraint, local markets will only prosper if they successfully find new sources of funds. Many municipal budgets have been badly affected by the global financial crisis. Consequently, cities need to look at innovative ways of securing the necessary funding. Conforming with this, in 2015 the Dutch Government announced its plan to send the *Dutch Urban Agenda* (or *Agenda Stad)* to parliament. This Agenda promotes the cooperation within and between urban regions.

The objective of this section is to show how the central government can use nonuniform tax reliefs to promote entry in small cities. I first assume a tax system that transfers funds from big to small cities (across cities). I compare the results with the effects of a tax system in which transfers are made from small to big markets (within cities). For simplicity, I do not allow tax reliefs to differ per type, as in the previous section. However, spillover effects are also incorporated since I base my entry predictions on the full model estimates.

Before explaining the policy experiment in more detail, I first define small and big cities based on population size. Small cities are municipalities with a total population below 15,000 inhabitants (first quartile). While big cities have a population larger than 27,000 people (last quartile). Similarly, I define small and big markets based on population size. Small markets are those with a population lower than 2,000, and big markets are those with population larger than 6,500 people, which constitutes the first and last quartile of population distribution at market level.

Given this classification, I estimate the entry predictions under a nonuniform tax scheme in which cafeterias and bars pay higher taxes (revenues drop by 40% ($\Delta = 0.6$)) in big cities, and receive a tax relief (revenues are increased by 30% ($\Delta = 1.3$)) in small ones. The transfer across cities, i.e., the size of Δ, is chosen such that the budget is balanced.[21] I follow the same simulation procedure explained in Subsection 2.6.1 to make entry predictions.

The second scenario is one in which funds are redistributed from big markets to small ones. The factors proposed are such that the amount of funds collected are roughly the same as in the previous scheme. Their values are, therefore, determined by the average revenue and number of businesses in each type of market. Specifically, I assume that bars and cafeterias in small markets receive a tax relief such that revenues are upward scaled by 60% ($\Delta = 1.6$), and those installed in big markets pay higher taxes such that revenues decreases in 15% ($\Delta = 0.85$).

Findings: Table 2.6 summarizes the results. As one could expect, the redistribution of funds across cities generates positive results for the small ones. For example, in term of coverage, 18 (11) markets that did not have any cafeteria (bar), now they have at least one. A similar positive effect is found in terms of the number of businesses: 88 new cafeterias and 75 new

[21] I estimate the amount of funds collected and redistributed by using the average revenues per bar and cafeteria and the total number of firms for big and small markets.

Table 2.6: Effects of different redistributive policies across vs. within cities

	Base	**Transfer across cities**		**Transfer within cities**	
Small cities	level	level	change	level	change
Coverage					
# markets with no cafeterias	93	75	-18	76	-17
# markets with no bars	55	44	-11	45	-10
# markets with none	36	27	-9	24	-12
# markets with 5+ retailers	57	74	17	57	0
Number of businesses					
# total businesses	987	1,150	163	1,042	55
# cafeterias	423	511	88	447	24
# bars	564	639	75	595	31
Medium size cities	level	level	change	level	change
Coverage					
# markets with no cafeterias	122	122	-	103	-19
# markets with no bars	82	82	-	72	-10
# markets with none	46	46	-	33	-13
# markets with 5+ retailers	132	132	-	129	-3
Number of businesses					
# total businesses	2,053	2,053	-	2,083	30
# cafeterias	956	956	-	967	11
# bars	1,097	1,097	-	1,116	19
Big cities	level	level	change	level	change
Coverage					
# markets with no cafeterias	72	109	37	60	-12
# markets with no bars	53	81	28	48	-5
# markets with none	27	49	22	19	-8
# markets with 5+ retailers	76	43	-33	74	-2
Number of businesses					
# total businesses	1,194	867	-327	1,214	20
# cafeterias	570	393	-177	578	8
# bars	624	475	-149	636	12
Country	level	level	change	level	change
Coverage					
# markets with no cafeterias	287	306	19	239	-48
# markets with no bars	190	207	17	165	-25
# markets with none	109	122	13	76	-33
# markets with 5+ retailers	265	249	-16	260	-5
Number of businesses					
# total businesses	4,234	4,071	-163	4,339	105
# cafeterias	1,949	1,860	-89	1,992	43
# bars	2,285	2,211	-74	2,347	62

Note: This table reports results based on entry predictions using the estimates of the full model. The first column shows the *status quo* prediction. All changes are measured with respect to that level. The 2nd and 3rd columns report the results when funds are transfered across cities: bars and cafeterias pay more taxes in big cities ($\Delta = 0.6$) and receive tax reliefs in small ones ($\Delta = 1.3$). The last two columns show results when redistribution happens from big markets ($\Delta = 0.85$) to small ones ($\Delta = 1.6$). The taxes are such that the amount of funds collected are the same in both scenarios (a more detailed explanation is found in the text).

bars enter small cities. Naturally, small cities become more attractive for firms to enter. Nevertheless, this comes at a high cost for big cities, where the number of businesses and coverage decreases more than what small cities gain. Medium size cities remain unchanged. The balance at country level is not positive.

About the second policy, the last two columns of Table 2.6 show that coverage in small cities increases in roughly the same magnitude when transfers are made from big to small markets. The number of firms entering also increases; the effect is lower than the one caused by transfers across cities though (+55 cafeterias and +31 bars). However, this policy leaves big and medium-size cities in better shape: both coverage and the number of businesses increase as well. The balance at country level results positive under this tax regime.

The reason behind these results is that both revenues and the number of firms are larger in big markets. This allows policymakers to collect funds without hurting less profitable businesses in small markets. Since cities pool markets of different sizes, redistributing funds across cities generates larger costs to less profitable businesses leading to a decrease in coverage and number of businesses at the country level. In sum, policymakers interested in making small cities more attractive should opt for a nonuniform tax scheme that redistributes funds from big to small markets.

2.7 Conclusion

Consumption amenities have become increasingly important for urban development. This paper uses unique administrative data on revenues and the number of firms to measure to what extent the presence of one amenity produces positive spillovers on another one. I extend previous free entry models and simultaneously estimate a static two-type entry model with revenue equations. Modelling the entry decision of both types allows me to directly control for unobserved characteristics that can be erroneously interpreted as spillovers.

In the context of cafeterias (take-away food places) and bars in the Netherlands, I find that spillover effects of entry are mainly unidirectional: the entry of bars positively affects the profitability of cafeterias, but not vice versa. This shows evidence that different amenity services may have asymmetric effects on other amenities when entering the market. Taking into account this asymmetry is relevant both for new entrant firms and policy makers. On the one hand, profit maximizing firms need to consider potential positive spillover effects when deciding on which location to enter. On the other hand, policy makers seeking to increase commercial activity in a certain area would improve the effectiveness of their policies by taking into consideration the right direction of spillovers. In addition, my results show that not accounting for endogeneity of entry decisions leads to a bias in the true intensity of spillover effects between different types of services. The net effect of this bias is manifested in the overestimation of spillover effects of cafeterias' entry on bars.

I perform two policy experiments that can provide useful insights to urban developers. First, I find that when the presence of spillover effects is ignored, urban policies will be inadequate. Policymakers who seek to encourage entry in less attractive areas will obtain more effective results -in terms of geographic coverage and number of businesses- by providing monetary incentives to the services that generate more spillover effects of entry (bars instead of cafeterias in this case). I also find that this is especially important in small markets.

Furthermore, in times of fiscal constraint, policymakers need to create innovative ways of securing funds that permit the provision of incentives in favor of less attractive areas. In my second policy experiment, I analyze the implications of different redistributive policies and find that it is more effective to redistribute funds within cities (from big to small markets) than across cities (from big to small cities). The results are mainly driven by the fact that both revenues and the number of firms are larger in big markets. This allows policymakers to collect funds without affecting less profitable businesses in small markets. Since cities pool markets of different sizes, when transfers are redistributed across cities, it generates larger costs to less profitable businesses located in big cities.

Appendix A. Likelihood function

In this section I show in more detail the likelihood contribution for different market configurations. There are three relevant cases, depending on the values of N_C and N_B. The model is a simultaneous bivariate ordered probit and demand model extended for two types. To estimate the model, I assume that $\varepsilon = (\omega_C, \omega_B, \xi_C, \xi_B)$ follow a tetravariate normal distribution $f(\cdot)$, with zero means and covariance matrix Σ

$$\Sigma = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} & \sigma_{\omega_C\xi_C} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} & \sigma_{\omega_B\xi_C} & \sigma_{\omega_B\xi_B} \\ \sigma_{\omega_C\xi_C} & \sigma_{\omega_B\xi_C} & \sigma^2_{\xi_C} & \sigma_{\xi_C\xi_B} \\ \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} & \sigma_{\xi_C\xi_B} & \sigma^2_{\xi_B} \end{bmatrix}$$

1. For markets without cafeterias or bars, i.e. $(N_C = 0, N_B = 0)$:

   - (r_C, r_B) unobserved

   - $$\begin{aligned} X\beta_C + \ln S + \theta^1_C &< \omega_C \\ X\beta_B + \ln S + \theta^1_B &< \omega_B \end{aligned}$$

   Therefore, the likelihood contribution is defined by

$$P(N_C = 0, N_B = 0) = \int_{\pi_C(1,0)}^{\infty} \int_{\pi_B(0,1)}^{\infty} f_{\omega_C,\,\omega_B}(u_C, u_B)\, \mathrm{d}u_C \mathrm{d}u_B$$

$$- \int_{\pi_C(1,0)}^{\pi_C(1,1)} \int_{\pi_B(0,1)}^{\pi_B(1,1)} f_{\omega_C,\,\omega_B}(u_C, u_B) \mathrm{d}u_C \mathrm{d}u_B$$

where $f_{\omega_C,\omega_B}(\cdot,\cdot)$ is the bivariate normal distribution of ω_C and ω_B, with zero mean and

$$\Sigma_{\omega_C\omega_B} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_B\omega_C} & \sigma^2_{\omega_B} \end{bmatrix}.$$

2. For markets with $(N_C > 0, N_B > 0)$:

   - $$\begin{aligned} \ln r_C &= X\lambda_C + \alpha_C^{N_C} + \frac{\delta_C^{N_B}}{N_C} + \xi_C \\ \ln r_B &= X\lambda_B + \alpha_B^{N_B} + \frac{\delta_B^{N_C}}{N_B} + \xi_B \end{aligned}$$

$$-\begin{array}{l} X\beta_C + \ln S + \theta_C^{N_C+1} + \gamma_C^{N_B} < \omega_C < X\beta_C + \ln S + \theta_C^{N_C} + \gamma_C^{N_B} \\ X\beta_B + \ln S + \theta_B^{N_B+1} + \gamma_B^{N_C} < \omega_B < X\beta_B + \ln S + \theta_B^{N_B} + \gamma_B^{N_C} \end{array}$$

The likelihood contribution is defined by

$$f(\ln r_C, \ln r_B, N_C = n_C, N_B = n_B)$$

$$= \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C,n_B)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C,n_B)} f_{\omega_C,\omega_B,\xi_C,\xi_B}(u_C, u_B, \xi_C, \xi_B)\, \mathrm{d}u_C \mathrm{d}u_B$$

$$- \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C+1,n_B+1)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C+1,n_B+1)} f_{\omega_C,\omega_B,\xi_C,\xi_B}(u_C, u_B, \xi_C, \xi_B)\, \mathrm{d}u_C \mathrm{d}u_B$$

where $\xi_i = \ln r_i - X\lambda_i - \alpha_i^{n_i} - \frac{\delta_i^{N_j}}{N_i}$. I estimate this likelihood as a product of (conditional) bivariate normals:

$$f(\omega_C, \omega_B, \xi_C, \xi_B) = f(\xi_C, \xi_B) \times f\big((\omega_C, \omega_B)|(\xi_C, \xi_B)\big).$$

Consequently, the likelihood contribution is redefined as

$$f(\ln r_C, \ln r_B)\, P((N_C = n_C, N_B = n_B)|(\ln r_C, \ln r_B))$$

$$= f(\xi_C, \xi_B) \times \Big(\int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C,n_B)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C,n_B)} f(u_C|(\xi_C, \xi_B), u_B|(\xi_C, \xi_B))\, \mathrm{d}u_C \mathrm{d}u_B$$

$$- \int_{\pi_C(n_C+1,n_B)}^{\pi_C(n_C+1,n_B+1)} \int_{\pi_B(n_C,n_B+1)}^{\pi_B(n_C+1,n_B+1)} f(u_C|(\xi_C, \xi_B), u_B|(\xi_C, \xi_B))\, \mathrm{d}u_C \mathrm{d}u_B \Big)$$

where $f(\xi_C, \xi_B)$ denotes the bivariate normal distribution of $\xi = (\xi_C, \xi_B)$ with zero mean and covariance

$$\Sigma_{\xi_C \xi_B} = \begin{bmatrix} \sigma_{\xi_C}^2 & \sigma_{\xi_C \xi_B} \\ \sigma_{\xi_C \xi_B} & \sigma_{\xi_B}^2 \end{bmatrix}.$$

$f(\omega_C|(\xi_C, \xi_B), \omega_B|(\xi_C, \xi_B))$ denotes the bivariate normal distribution of ω_C and ω_B given $\xi = (\xi_C, \xi_B)$, with conditional expectation $\mu_{\omega.\xi}$, and conditional covariance $\Sigma_{\omega.\xi}$. To obtain $\mu_{\omega.\xi}$ and $\Sigma_{\omega.\xi}$, I split Σ, such that

$$\Sigma = \begin{bmatrix} \Sigma_{\omega\omega} & \Sigma_{\omega\xi} \\ \Sigma_{\xi\omega} & \Sigma_{\xi\xi} \end{bmatrix}.$$

Then,

$$\mu_{\omega.\xi} = \mu_\omega + \Sigma_{\omega\xi}\Sigma_{\xi\xi}^{-1}(\xi - \mu_\xi)$$

$$\Sigma_{\omega.\xi} = \Sigma_{\omega\omega} - \Sigma_{\omega\xi}\Sigma_{\xi\xi}^{-1}\Sigma_{\xi\omega}$$

Σ is symmetric, therefore $\Sigma_{\xi\omega} = \Sigma_{\omega\xi}$.

In more detail, the conditional mean of (ω_C, ω_B), given (ξ_C, ξ_B) is

$$\mu_{\omega.\xi} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \sigma_{\omega_C\xi_C} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_C} & \sigma_{\omega_B\xi_B} \end{bmatrix} \begin{bmatrix} \sigma^2_{\xi_C} & \sigma_{\xi_C\xi_B} \\ \sigma_{\xi_C\xi_B} & \sigma^2_{\xi_B} \end{bmatrix}^{-1} \begin{bmatrix} \xi_C - 0 \\ \xi_B - 0 \end{bmatrix}$$

$$\mu_{\omega.\xi} = \begin{bmatrix} \sigma_{\omega_C\xi_C} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_C} & \sigma_{\omega_B\xi_B} \end{bmatrix} \frac{\begin{bmatrix} \sigma^2_{\xi_B} & -\sigma_{\xi_C\xi_B} \\ -\sigma_{\xi_C\xi_B} & \sigma^2_{\xi_C} \end{bmatrix}}{\det \Sigma_{\xi\xi}} \begin{bmatrix} \xi_C \\ \xi_B \end{bmatrix}$$

Since $\det \Sigma_{\xi\xi} = \sigma^2_{\xi_C}\sigma^2_{\xi_B} - \sigma^2_{\xi_C\xi_B}$, then

$$\mu_{\omega.\xi} = \frac{1}{\det \Sigma_{\xi\xi}} \begin{bmatrix} \sigma_{\omega_C\xi_C} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_C} & \sigma_{\omega_B\xi_B} \end{bmatrix} \begin{bmatrix} \sigma^2_{\xi_B} & -\sigma_{\xi_C\xi_B} \\ -\sigma_{\xi_C\xi_B} & \sigma^2_{\xi_C} \end{bmatrix} \begin{bmatrix} \xi_C \\ \xi_B \end{bmatrix}$$

$$\mu_{\omega.\xi} = \frac{1}{\det \Sigma_{\xi\xi}} \begin{bmatrix} \sigma_{\omega_C\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_C\xi_B}\sigma_{\xi_C\xi_B} & -\sigma_{\omega_C\xi_C}\sigma_{\xi_C\xi_B} + \sigma_{\omega_C\xi_B}\sigma_{\xi^2_C} \\ \sigma_{\omega_B\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_B\xi_B}\sigma_{\xi_C\xi_B} & -\sigma_{\omega_B\xi_C}\sigma_{\xi_C\xi_B} + \sigma_{\omega_B\xi_B}\sigma^2_{\xi_C} \end{bmatrix} \begin{bmatrix} \xi_C \\ \xi_B \end{bmatrix}$$

$$\mu_{\omega.\xi} = \begin{bmatrix} \mu_{\omega_C.\xi} \\ \mu_{\omega_B.\xi} \end{bmatrix} = \frac{1}{\det \Sigma_{\xi\xi}} \begin{bmatrix} (\sigma_{\omega_C\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_C\xi_B}\sigma_{\xi_C\xi_B})\xi_C + (\sigma_{\omega_C\xi_B}\sigma^2_{\xi_C} - \sigma_{\omega_C\xi_C}\sigma_{\xi_C\xi_B})\xi_B \\ (\sigma_{\omega_B\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_B\xi_B}\sigma_{\xi_C\xi_B})\xi_C + (\sigma_{\omega_B\xi_B}\sigma^2_{\xi_C} - \sigma_{\omega_B\xi_C}\sigma_{\xi_C\xi_B})\xi_B \end{bmatrix}$$

The conditional variance of (ω_C, ω_B), given (ξ_C, ξ_B) takes the form

$$\Sigma_{\omega.\xi} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} \end{bmatrix}$$
$$- \tfrac{1}{\det \Sigma_{\xi\xi}} \begin{bmatrix} \sigma_{\omega_C\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_C\xi_B}\sigma_{\xi_C\xi_B} & -\sigma_{\omega_C\xi_C}\sigma_{\xi_C\xi_B} + \sigma_{\omega_C\xi_B}\sigma_{\xi^2_C} \\ \sigma_{\omega_B\xi_C}\sigma^2_{\xi_B} - \sigma_{\omega_B\xi_B}\sigma_{\xi_C\xi_B} & -\sigma_{\omega_B\xi_C}\sigma_{\xi_C\xi_B} + \sigma_{\omega_B\xi_B}\sigma^2_{\xi_C} \end{bmatrix} \begin{bmatrix} \sigma_{\omega_C\xi_C} & \sigma_{\omega_B\xi_C} \\ \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} \end{bmatrix}$$

Hence,

$$\Sigma_{\omega.\xi} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} \end{bmatrix} - \frac{1}{\det \Sigma_{\xi\xi}} \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

$$\Sigma_{\omega.\xi} = \begin{bmatrix} \sigma_{\omega_C\omega_C.\xi} & \sigma_{\omega_C\omega_B.\xi} \\ \sigma_{\omega_C\omega_B.\xi} & \sigma_{\omega_B\omega_B.\xi} \end{bmatrix} = \begin{bmatrix} \sigma^2_{\omega_C} - \frac{a}{\det\Sigma_{\xi\xi}} & \sigma_{\omega_C\omega_B} - \frac{b}{\det\Sigma_{\xi\xi}} \\ \sigma_{\omega_C\omega_B} - \frac{c}{\det\Sigma_{\xi\xi}} & \sigma^2_{\omega_B} - \frac{d}{\det\Sigma_{\xi\xi}} \end{bmatrix}$$

with

$$\begin{aligned}
a &= \sigma^2_{\omega_1\xi_1}\sigma^2_{\xi_2} - \sigma_{\omega_1\xi_1}\sigma_{\omega_1\xi_2}\sigma_{\xi_1\xi_2} - \sigma_{\omega_1\xi_1}\sigma_{\omega_1\xi_2}\sigma_{\xi_1\xi_2} + \sigma^2_{\omega_1\xi_2}\sigma_{\xi_1^2}, \\
b &= \sigma_{\omega_2\xi_1}\sigma_{\omega_1\xi_1}\sigma^2_{\xi_2} - \sigma_{\omega_2\xi_1}\sigma_{\omega_1\xi_2}\sigma_{\xi_1\xi_2} - \sigma_{\omega_2\xi_2}\sigma_{\omega_1\xi_1}\sigma_{\xi_1\xi_2} + \sigma_{\omega_2\xi_2}\sigma_{\omega_1\xi_2}\sigma_{\xi_1^2}, \\
c &= \sigma_{\omega_1\xi_1}\sigma_{\omega_2\xi_1}\sigma^2_{\xi_2} - \sigma_{\omega_1\xi_1}\sigma_{\omega_2\xi_2}\sigma_{\xi_1\xi_2} - \sigma_{\omega_1\xi_2}\sigma_{\omega_2\xi_1}\sigma_{\xi_1\xi_2} + \sigma_{\omega_1\xi_2}\sigma_{\omega_2\xi_2}\sigma^2_{\xi_1}, \\
d &= \sigma^2_{\omega_2\xi_1}\sigma^2_{\xi_2} - \sigma_{\omega_2\xi_1}\sigma_{\omega_2\xi_2}\sigma_{\xi_1\xi_2} - \sigma_{\omega_2\xi_2}\sigma_{\omega_2\xi_1}\sigma_{\xi_1\xi_2} + \sigma^2_{\omega_2\xi_2}\sigma^2_{\xi_1}.
\end{aligned}$$

3. Finally, for mixed cases such that ($N_C = 0, N_B > 0$) or ($N_C = 0, N_B > 0$). To illustrate, for markets with ($N_C = 0, N_B > 0$):

- r_C unobserved

  $\ln r_B = X\lambda_B + \alpha_B^{N_B} + \xi_B$

- $$\begin{aligned} X\beta_C + \ln S + \theta_C^1 + \gamma_C^{N_B} &< \omega_C \\ X\beta_B + \ln S + \theta_B^{N_B+1} &< \omega_B < X\beta_B + \ln S + \theta_B^{N_B} \end{aligned}$$

The likelihood contribution is given by

$$f(\ln r_B, N_C = 0, N_B = n_B) = \int_{\pi_C(1,n_B)}^{\infty} \int_{\pi_B(0,n_B+1)}^{\pi_B(0,n_B)} f_{\omega_C,\omega_B,\xi_B}(u_C, u_B, \xi_B)\mathrm{d}u_C\mathrm{d}u_B$$

$$- \int_{\pi_C(1,n_B)}^{\pi_1(1,n_B+1)} \int_{\pi_B(0,n_B+1)}^{\pi_B(1,n_B+1)} f_{\omega_C,\omega_B,\xi_B}(u_C, u_B, \xi_B)\,\mathrm{d}u_C\mathrm{d}u_B$$

where $\xi_B = \ln r_B - X\lambda_B - \alpha_B^{n_B}$. $f_{\omega_C,\omega_B,\xi_B}(.,.,.)$ denotes the joint density of ω_C,ω_B and ξ_B. Given that $(\omega_C, \omega_B, \xi_C, \xi_B)$ distribute as a multivariate normal with zero means and covariance matrix Σ, $(\omega_C, \omega_B, \xi_C)$ distribute as a trivariate normal with zero means and covariance matrix defined by

$$\Sigma_{\omega\xi_B} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} & \sigma_{\omega_B\xi_B} \\ \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} & \sigma^2_{\xi_B} \end{bmatrix}.$$

Similar to the previous case, one can write the joint density as the product of a conditional density and a marginal density, i.e., $f(\omega_C, \omega_B, \xi_B) = f((\omega_C, \omega_B)|\xi_B)\, f(\xi_B)$, with $\xi_B \sim N[0, \sigma^2_{\xi_B}]$. $f((\omega_C, \omega_B)|\xi_B)$ stands for the conditional density of a bivariate normal with mean $\mu_{\omega_C\omega_B.\xi_B}$ and covariance $\Sigma_{\omega_C\omega_B.\xi_B}$. One can split $\Sigma_{\omega\xi_B}$ such that

$$\Sigma_{\omega\xi_B} = \left[\begin{array}{cc|c} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} & \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} & \sigma_{\omega_B\xi_B} \\ \hline \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} & \sigma^2_{\xi_B} \end{array}\right] = \begin{bmatrix} \Sigma_{\omega\omega} & \Sigma_{\omega\xi_B} \\ \Sigma_{\xi_B\omega} & \Sigma_{\xi_B\xi_B} \end{bmatrix}$$

Then, the conditional mean is defined by

$$\mu_{\omega.\xi_B} = \mu_\omega + \Sigma_{\omega\xi_B}\Sigma^{-1}_{\xi_B\xi_B}(\xi_B - \mu_{\xi_B})$$

$$\mu_{\omega.\xi_B} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \begin{bmatrix} \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_B} \end{bmatrix} (\sigma^2_{\xi_B})^{-1}(\xi_B - 0)$$

$$\mu_{\omega.\xi_B} = \begin{bmatrix} \mu_{\omega_C|\xi_B} \\ \mu_{\omega_B|\xi_B} \end{bmatrix} = \begin{bmatrix} \frac{\sigma_{\omega_C\xi_B}}{\sigma^2_{\xi_B}}\xi_B \\ \frac{\sigma_{\omega_B\xi_B}}{\sigma^2_{\xi_B}}\xi_B \end{bmatrix}$$

And the conditional variance of (ω_1, ω_2), given ξ_2 is

$$\Sigma_{\omega.\xi_B} = \Sigma_{\omega\omega} - \Sigma_{\omega\xi_B}\Sigma^{-1}_{\xi_B\xi_B}\Sigma_{\xi_B\omega}$$

$$\Sigma_{\omega.\xi_2} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} \end{bmatrix} - \begin{bmatrix} \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_B} \end{bmatrix} (\sigma^2_{\xi_B})^{-1} \begin{bmatrix} \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} \end{bmatrix}$$

$$\Sigma_{\omega.\xi_B} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} \end{bmatrix} - \frac{1}{\sigma^2_{\xi_B}} \begin{bmatrix} \sigma_{\omega_C\xi_B} \\ \sigma_{\omega_B\xi_B} \end{bmatrix} \begin{bmatrix} \sigma_{\omega_C\xi_B} & \sigma_{\omega_B\xi_B} \end{bmatrix}$$

$$\Sigma_{\omega.\xi_B} = \begin{bmatrix} \sigma^2_{\omega_C} & \sigma_{\omega_C\omega_B} \\ \sigma_{\omega_C\omega_B} & \sigma^2_{\omega_B} \end{bmatrix} - \frac{1}{\sigma^2_{\xi_B}} \begin{bmatrix} \sigma^2_{\omega_C\xi_B} & \sigma_{\omega_C\xi_B}\sigma_{\omega_B\xi_B} \\ \sigma_{\omega_C\xi_B}\sigma_{\omega_B\xi_B} & \sigma^2_{\omega_B\xi_B} \end{bmatrix}$$

$$\Sigma_{\omega.\xi_2} = \begin{bmatrix} \sigma^2_{\omega_C} - \frac{\sigma^2_{\omega_C\xi_B}}{\sigma^2_{\xi_B}} & \sigma_{\omega_C\omega_B} - \frac{\sigma_{\omega_C\xi_B}\sigma_{\omega_B\xi_B}}{\sigma^2_{\xi_B}} \\ \sigma_{\omega_C\omega_B} - \frac{\sigma_{\omega_C\xi_B}\sigma_{\omega_B\xi_B}}{\sigma^2_{\xi_B}} & \sigma^2_{\omega_B} - \frac{\sigma^2_{\omega_B\xi_B}}{\sigma^2_{\xi_B}} \end{bmatrix}.$$

Appendix B. Parameter estimates from full model

Variables	Cafeterias		Bars	
Entry equation				
Income per capita	-0.031***	(0.011)	-0.059	(0.050)
Density	-0.003	(0.041)	-0.005	(0.024)
Fraction of households with children	-1.847**	(0.689)	2.939***	(0.337)
Fraction of children	-3.270	(2.932)	-11.949***	(2.273)
Fraction of young	-5.873***	(1.146)	-4.631***	(0.362)
Fraction of old	-0.439	(0.287)	3.404***	(0.524)
Total retail locations	0.088	(0.075)	0.017	(0.067)
N. supermarkets	0.020	(0.031)	-0.142***	(0.031)
θ^1 ($N_i = 1$)	-5.385***	(0.231)	-4.131***	(1.360)
θ^2	-6.369***	(0.229)	-5.240***	(1.331)
θ^3	-7.040***	(0.233)	-6.085***	(1.160)
θ^4	-7.565***	(0.332)	-6.836***	(1.392)
θ^5	-8.080***	(0.333)	-7.405***	(1.380)
γ^1 ($N_j = 1$)	0.413***	(0.098)	2.6E-04	(0.635)
γ^2	0.672***	(0.061)	9.6E-04	(0.630)
γ^3	0.847***	(0.132)	1.0E-03	(0.965)
γ^4	1.111***	(0.314)	0.228	(0.424)
γ^5	1.392***	(0.264)	0.760***	(0.226)
Revenue equation				
Income per capita	-0.017*	(0.009)	-0.009	(0.014)
Density	-0.010	(0.041)	-0.004	(0.034)
Fraction of households with children	0.277***	(0.090)	3.003***	(0.647)
Fraction of children	-3.131***	(1.029)	-4.826***	(0.300)
Fraction of young	-0.236	(0.591)	-1.185***	(0.273)
Fraction of old	0.735	(0.696)	4.416**	(1.649)
Total retail locations	-0.022	(0.079)	-0.002	(0.026)
N. supermarkets	0.003	(0.014)	-0.053	(0.039)
α^1 ($N_i = 1$)	4.596***	(0.432)	3.460***	(0.739)
α^2	4.283***	(0.521)	3.179***	(0.799)
α^3	4.137***	(0.728)	2.961***	(0.651)
α^4	3.876***	(0.671)	2.729***	(0.698)
α^5	3.569***	(0.626)	-0.183	(0.224)
δ^1 ($N_j = 1$)	0.009	(0.215)	-0.054	(0.240)
δ^2	0.013	(0.209)	-0.298	(0.346)
δ^3	-0.089	(0.356)	-0.298	(0.799)
δ^4	0.188	(0.474)	-0.553	(0.475)
δ^5	-0.157	(0.126)	2.166***	(0.741)
Covariance matrix				
σ_{ω_C}	1.032***	(0.129)		
σ_{ω_B}	1.462***	(0.080)		
σ_{ξ_C}	0.706***	(0.019)		
σ_{ξ_B}	0.869***	(0.022)		
$\sigma_{\omega_C \omega_B}$	-0.286***	(0.088)		
$\sigma_{\omega_C \xi_C}$	-0.341*	(0.200)		
$\sigma_{\omega_C \xi_B}$	0.059	(0.050)		
$\sigma_{\omega_B \xi_C}$	-0.227**	(0.109)		
$\sigma_{\omega_B \xi_B}$	-0.861***	(0.086)		
$\sigma_{\xi_C \xi_B}$	0.159**	(0.076)		
N. observations				1,005
Log likelihood				-4,352.8

Note: This table reports the estimates from the two-type entry and revenue model. The parameters are estimated by maximum likelihood. Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Appendix C. Sensitivity analysis: different market definition

Variables	Cafeterias		Bars	
Entry equation				
Income per capita	-0.032	(0.036)	-0.060***	(0.017)
Density	-0.009	(0.085)	-0.002	(0.033)
Fraction of households with children	-2.067	(0.284)	2.937***	(0.272)
Fraction of children	-3.273***	(0.715)	-12.113***	(2.153)
Fraction of young	-6.633***	(1.327)	-4.754***	(1.178)
Fraction of old	-0.693***	(0.223)	2.550***	(0.262)
Total retail locations	0.102	(0.107)	0.004	(0.066)
N. supermarkets	0.031	(0.070)	-0.148	(0.071)
θ^1 $(N_i = 1)$	-5.262***	(0.379)	-3.944	(0.250)
θ^2	-6.292***	(0.317)	-5.022	(0.293)
θ^3	-6.995***	(0.407)	-5.842	(0.313)
θ^4	-7.551***	(0.323)	-6.548	(0.325)
θ^5	-8.129***	(0.398)	-7.101	(0.346)
γ^1 $(N_j = 1)$	0.480***	(0.140)	0.009	(0.309)
γ^2	0.794***	(0.078)	0.010	(0.318)
γ^3	1.029***	(0.055)	0.010	(0.512)
γ^4	1.339***	(0.156)	0.220	(0.135)
γ^5	1.653***	(0.154)	0.642***	(0.117)
Revenue equation				
Income per capita	-0.016**	(0.009)	-0.010	(0.016)
Density	-0.011	(0.031)	-0.003	(0.035)
Fraction of households with children	0.127	(0.141)	3.086***	(0.319)
Fraction of children	-3.301**	(1.439)	-5.013***	(0.648)
Fraction of young	0.336	(0.355)	-1.499***	(0.314)
Fraction of old	0.248**	(0.118)	3.864***	(1.086)
Total retail locations	-0.023	(0.029)	-0.006	(0.109)
N. supermarkets	-0.005	(0.024)	-0.059	(0.040)
α^1 $(N_i = 1)$	4.726***	(0.265)	3.591***	(0.386)
α^2	4.399***	(0.243)	3.319***	(0.412)
α^3	4.269***	(0.167)	3.111***	(0.320)
α^4	4.005***	(0.243)	2.905***	(0.385)
α^5	3.709***	(0.157)	-0.151	(0.552)
δ^1 $(N_j = 1)$	-0.021	(0.084)	-0.037	(0.145)
δ^2	-0.021	(0.185)	-0.267**	(0.115)
δ^3	-0.121	(0.108)	-0.258	(0.600)
δ^4	0.182	(0.134)	-0.511***	(0.135)
δ^5	-0.179**	(0.088)	2.348***	(0.282)
Covariance matrix				
σ_{ω_C}			1.084***	(0.041)
σ_{ω_B}			1.405***	(0.125)
σ_{ξ_C}			0.693***	(0.041)
σ_{ξ_B}			0.863***	(0.092)
$\sigma_{\omega_C \omega_B}$			-0.392***	(0.062)
$\sigma_{\omega_C \xi_C}$			-0.330***	(0.083)
$\sigma_{\omega_C \xi_B}$			0.112*	(0.055)
$\sigma_{\omega_B \xi_C}$			-0.202***	(0.040)
$\sigma_{\omega_B \xi_B}$			-0.810***	(0.264)
$\sigma_{\xi_C \xi_B}$			0.146***	(0.031)
N. observations				989
Log likelihood				-4,267.4

Note: This table reports the full model estimates under an alternative market definition in which I exclude city centers from my sample (see the justification for this robustness check in Section 2.5). Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Appendix D. Entry thresholds per firm

Table 2.7: One-type model: entry thresholds per firm

ET cafeterias	N_B=0	N_B=1	N_B=2	N_B=3	N_B=4	N_B=5
N_C=1	2,242	1,317	1,058	880	605	410
N_C=2	2,635	1,548	1,244	1,034	711	482
N_C=3	3,151	1,852	1,487	1,237	851	576
N_C=4	3,580	2,103	1,689	1,405	966	655
ET bars	N_C=0	N_C=1	N_C=2	N_C=3	N_C=4	N_C=5
N_B=1	1,017	796	723	600	323	119
N_B=2	1,726	1,350	1,226	1,019	547	202
N_B=3	2,912	2,278	2,069	1,719	924	340
N_B=4	4,905	3,837	3,485	2,895	1,556	573

Note: This table reports the estimated entry thresholds per firm for each market configuration, using the parameter estimates from the one-type entry model with revenue equation (baseline model). Entry thresholds per firm indicates how many people per firm is needed to support a certain number of cafeterias (bars) in the market, for a given number of bars (cafeterias).

Table 2.8: Full two-type model: entry thresholds per firm

ET cafeterias	N_B=0	N_B=1	N_B=2	N_B=3	N_B=4	N_B=5
N_C=1	2,627	1,738	1,342	1,127	866	653
N_C=2	3,511	2,323	1,794	1,507	1,157	873
N_C=3	4,578	3,030	2,339	1,965	1,509	1,139
N_C=4	5,807	3,843	2,967	2,492	1,913	1,445
ET bars	N_C=0	N_C=1	N_C=2	N_C=3	N_C=4	N_C=5
N_B=1	827	826	826	826	658	350
N_B=2	1,253	1,252	1,251	1,251	997	530
N_B=3	1,945	1,945	1,943	1,943	1,548	823
N_B=4	3,089	3,088	3,086	3,086	2,458	1,307

Note: This table reports the estimated entry thresholds per firm for each market configuration, using the parameter estimates from the two-type entry model with revenue equations. Entry thresholds per firm indicates how many people per firm is needed to support a certain number of cafeterias (bars) in the market, for a given number of bars (cafeterias).

Appendix E. Counterfactual analysis

Table 2.9: Entry predictions under alternative tax relief schemes

Total sample		$\Delta_C = 1.25$		$\Delta_B = 1.25$	
	No change	level	change	level	change
Coverage					
# markets with no cafeterias	287	245	-42	276	-11
# markets with no bars	190	188	-2	157	-33
# markets with none	109	98	-11	90	-19
# markets with max. 2 retailers	362	333	-29	328	-34
# markets with 5+ retailers	265	297	32	297	32
Number of businesses					
# total businesses	4,234	4,504	270	4,509	275
# cafeterias	1,949	2,183	234	2,009	60
# bars	2,285	2,321	36	2,500	215
Small markets					
Coverage					
# markets with no cafeterias	255	223	-32	247	-8
# markets with no bars	142	142	0	120	-22
# markets with none	101	92	-9	84	-17
# markets with max. 2 retailers	289	273	-16	267	-22
# markets with 5+ retailers	44	50	6	55	11
Number of businesses					
# total businesses	1,232	1,330	98	1,356	124
# cafeterias	423	514	91	446	23
# bars	809	816	7	910	101
Big markets					
Coverage					
# markets with no cafeterias	32	22	-10	29	-3
# markets with no bars	48	46	-2	37	-11
# markets with none	8	6	-2	6	-2
# markets with max. 2 retailers	73	60	-13	61	-12
# markets with 5+ retailers	221	247	26	242	21
Number of businesses					
# total businesses	3,002	3,174	172	3,153	151
# cafeterias	1,526	1,669	143	1,563	37
# bars	1,476	1,505	29	1,590	114

Note: This table reports the entry predictions under two alternative tax regimes. The first column shows the status quo prediction. All changes are measured with respect to that level. The second and third column report the results when policies exclusively increase cafeterias' revenue in 25% (revenues are multiplied by a factor $\Delta_C = 1.25$). Likewise, the last two columns show changes when bars are the only ones benefiting ($\Delta_B = 1.25$).

3 | The competitive effect of entry in mobile markets

3.1 Introduction

The existence of first-mover advantages influences the dynamics of competition in the mobile industry. Lieberman and Montgomery (1988) explain that such advantages arise endogenously within a multi-stage process, where some asymmetry is generated in the first stage. This first-mover opportunity enables early entrants to benefit from a head start over rivals. Once this asymmetry is generated, firms may use a variety of mechanisms to exploit their positions, thus enhancing the profits' magnitude or durability (or both).

There are several reasons why first-mover advantages may exist in mobile markets.[1] On the demand side, switching costs and network externalities bind customers to firms if products are incompatible, locking them into early choices (Farrell and Klemperer (2007), Klemperer (1987)). First-mover advantages are also associated to the recognition of (and loyalty to) the brand (Schmalensee (1982), Gerpott et al. (2001)). On the supply side, there are also many factors explaining the competitive advantage of early entrants in the market, such as sunk costs and economies of scale (Schmalensee (1981)). Moreover, later entrants need time to build a reliable network creating coverage differences that put them in disadvantage with respect to incumbents. Finally, later entrants deal with less availability of land space to install antennas.

In this paper, I study how first-mover advantages shape the competitive dynamics in mobile markets, once an important technological change occurs, as it is the introduction of digital-based systems. In particular, I measure incumbents' and entrants' strength of competition. To this end, I estimate a static-two type entry model in which digital cellular incumbents compete

[1] A more detailed overview about the determinants of first-mover advantages (demand- an supply-side factors) is provided in Section 3.2.

with new digital operators (Personal Communications Services (PCS) entrants and Nextel). The model is inspired by Greenstein and Mazzeo (2006), who analyzed the competitive dynamics between regional and national competitive local exchange carriers (CLECs) in the U.S. in 1999 and 2002. As in previous empirical works, I assume that the outcome of the static equilibrium game provides a reasonable first approximation to the underlying repeated interaction among firms. The entry model is also related to Mazzeo (2002) and Cleeren et al. (2010) by allowing for asymmetric competitive effects.

Although first-mover advantages exist, it is unclear whether incumbents exert stronger competitive impact on entrants' profits than vice versa. New competitors may follow marketing strategies to counteract incumbents' advantage. For example, the Federal Communication Commission (FCC) reports that at the time new digital carriers launched their systems, they offered plans with several price promotions to compensate consumers for their lack of coverage (FCC (1997)). Moreover, later entrants fought against incumbents' brand-prestige by offering new services that seemed attractive in opposition to incumbents' offer. New carriers offered, for instance, "free-contracts" that allowed consumers to quite terminate their contract at any point in time without having to pay extra termination fees. Incumbents, on the other hand, were known for offering long-term contracts. Finally, entrants into local mobile markets are not necessarily weak competitors since many of them were previously operating in different geographical areas.

The introduction of digital-based technology in the United States creates an ideal setting to understand the dynamics of competition under the presence of first-mover advantages. First of all, new competitors entered the market after the U.S. government decided to award new spectrum bands for the deployment of digital mobile services. The FCC started the licensing process of 120 MHz of spectrum for Broadband PCS in 1994. This process not only gave room to entry of up to six new digital players in each local market, but it also motivated installed analog firms to take preemptive strategies and upgrade their systems to digital technology (Meyers (1997)). Also, the FCC imposed on every PCS licensee to serve between 25% to 33% of the market's population within 5 years. Thanks to this licensing process, I am thus able to measure the competitive interaction between incumbents and entrants that choose to provide the services afterwards. The majority of empirical studies on first-mover advantages estimate the effect of the order of entry on market shares (market pioneers have substantially higher market shares than later entrants). However, the strong association between order of entry and market share is questioned because a firm's timing of entry might be a choice variable that depends on the perceived market expectations after entry (Bijwaard et al. (2008)). In this paper, I focus on the stage that followed the awarding process and use an alternative framework to measure the effects of first-mover advantages on the dynamics of competition.

Secondly, the FCC divided the country into different non-overlapping market areas to award spectrum. This allows me to observe variability on entry choices, and relate them to different market characteristics. More importantly, it assures a correct estimation of the competitive effect among carriers installed in the market. Finally, the disruptive property of this technology somehow forms a level-playing field among operators. Digital systems make possible a more efficient use of the spectrum, and facilitate the offering of a broader array of wireless services, such as paging, short message service (SMS), voice-mail and caller ID. For this reason, I model exclusively the digital firms' entry choices. In other words, the entry choice of analog firms is not included in the model, but I do consider their competitive effect as substitute technology to specify digital firms' payoffs.

Given the increasing importance that mobile service has acquired, most of the empirical literature has focused on studying which factors have determined its diffusion (Gruber and Verboven (2001), Gruber (2001), Koski and Kretschmer (2005)). In general, the debate centered on how and when entry should be promoted. It also studied whether a technology standard should be imposed centrally (e.g. GSM technology in Europe), or selected by the market forces in a decentralized way, such as digital technologies in the U.S., where three different and incompatible standards (CDMA, TDMA, GSM) were installed by mobile operators. For example, Gruber and Verboven (2001) study the effect of regulatory intervention on technological standardization and timing of entry to analyze the impact on diffusion. Gruber (2001) studies the effect of the total number of competitors, the timing of initial adoption, and the speed of adoption over the speed of diffusion. Both studies used cross sectional data of different countries to compare the impact of various factors on the growth rate of mobile service.

Only a few empirical studies have studied the strength of competition in the mobile industry. Bijwaard et al. (2008) examined the existence of first-mover advantages by using dynamic and static models of market share for 16 European mobile markets from 1990 to 2006. During this period, different technologies were used (1G in the early and mid 1990s, 2G from late 1990s until the introduction of 3G near 2006), but no technological distinction was made. They estimated the impact of market concentration (Herfindahl-Hirschman Index) and penetration rates on the development of market shares of entrant firms. Their results showed evidence of early-mover advantages, mainly caused by the influence of the penetration rate. In other words, it pays to enter when still few people have contracted mobile service. They also found that it is significantly easier to enter a highly concentrated industry.

Seim and Viard (2011) provide the closest empirical research for the purpose of my study. First, using the U.S. mobile markets between 1996 and 1998, they measured the effect of PCS digital competitors on analog companies' decision to convert to digital systems. Second, they also analyzed the change of price discrimination strategies that firms used. They found that in markets with more competition, analog firms are more likely to upgrade their systems and phase out their analog plans. Furthermore, firms' entry causes an increase in the number of plans, and in the amount of discounts offered, specially for high-usage consumers. Seim and Viard (2011) also provided some insights about the strategies of competition followed by mobile firms. They found that competition forced analog companies to serve low-usage clients and digital companies to serve high-usage clients. Given their capacity constrains, analog companies served better low-usage clients while digital companies could more effectively meet the needs of high-usage clients.

My study attempts to complement these findings by measuring the competitive interaction among firms once they adopt digital technologies. My findings suggest that digital firms' entry choices are strategic substitutes. This means that the entry of an additional digital firm decreases competitors' payoffs. Concerning the strength of competition, I find that incumbent cellular operators exert a significantly negative effect on PCS entrants' payoffs. On the other hand, the entry effect of new PCS providers on incumbents' profitability is negative but not statistically significant. Therefore, this is in line with the presence of first-mover advantages in favor of digital incumbents.

The rest of this paper is structured as follows. Section 3.2 contains information about the U.S. digital mobile markets. Section 3.3 describes the data. Section 3.4 explains the empirical methodology. Section 3.5 provides the results. Finally, Section 4.5 concludes with a brief summary of the main findings.

3.2 The deployment of digital mobile services in the U.S.

In the United States, as in many other countries, the entry of new firms into mobile industry has been closely related to the introduction of new technologies that allowed a more efficient use of the radio spectrum. Regulatory policies related to the use of technological standards and the timing of entry have also had an important effect on the dynamics of competition.

One of the most important technological changes experienced in the 1990s was the introduction of digital technologies to replace analog systems. Analog systems, also called first-generation (1G) systems, used the allocated radio spectrum in a relatively inefficient manner.

The introduction of digital technologies led to a change in performance, capacity and quality of mobile telecommunications. This innovation first included second-generation systems (2G) and gradually evolved to third (3G) and fourth (4G) generation systems. Through easier computer regeneration of digital pulses, it improved capacity and sound quality of voice transmission. Moreover, these systems allowed operators to offer new data services, such as SMS, call waiting and caller ID. It also allowed to secure privacy of conversations (Gruber (2005)). Finally, by allowing these new features, digital technology increased vertical differentiation in providing the service.[2]

Before digital technology was introduced in the U.S. mobile industry, two cellular companies were operating in each local market. In 1981, the FCC licensed two competing cellular systems in every Cellular Market Area (CMA).[3] Thus, one system was to be operated by a separate subsidiary of a local telephone company, and the other was to be unaffiliated from any local telephone company (FCC (1995)). At that time, mobile service was conceived almost exclusively for business use. The introduction of digital systems, given its more efficient use of the spectrum, made it possible for mobile operators to target their marketing strategies to the mass consumer market. It, consequently, increased the size of the market and made entry more attractive.

Cellular carriers used a specific analog standard called Advanced Mobile Phone System (AMPS). The FCC imposed this standard to facilitate subscribers to switch carriers without having to buy new equipment. In 1988, this regulation was relaxed and cellular carriers were permitted to adopt new technologies, as long as they continued to support their analog systems. This decision was meant to encourage the development of new digital equipment that enables to increase the existing channels' capacity. Digital technology, however, was not introduced until the licensing process of digital PCS spectrum started in 1994. At that time, some operators upgraded their systems as a preemptive competitive strategy against the entry of future digital competitors. By 1996, cellular firms installed different incompatible digital technologies: Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA).

In the early 1990s, the FCC also allocated 120 MHz of spectrum for Broadband Personal Communications Services (PCS) to facilitate the entrance of new competitors in the market.[4] The geographic market definition for this new licensing process differed from the one used for

[2]Prior to the introduction of digital technology, vertical differentiation was primarily due to differences in call quality in the local calling area (FCC (1997)).

[3]CMA is the geographic market definition used by the FCC to award those licenses. There were 306 metropolitan statistical areas (MSA), and 428 rural service areas (RSA) covering the entire country.

[4]The FCC allowed the entrance of a maximum of 6 new competitors in each market.

cellular operators. The FCC divided the country into 51 Major Trading Areas (MTAs), which contained multiple cities or states. The MTAs were further subdivided into 493 Basic Trading Areas (BTAs).[5]

The spectrum was divided into 6 bands: 3 bands of 30 MHz each -called Blocks A, B and C-, and 3 bands of 10 MHz -Blocks D, E, and F-. By June 1995, the FCC had licensed Blocks A and B for the 51 MTAs. The A and B Block auctions were open to all interested bidders. The majority of these licenses went to companies or joint ventures of companies that were already established in the cellular business. Several cellular carriers used broadband PCS licenses to expand the size of their network. To ensure competition, the FCC established that cellular carriers should not obtain more than 10 MHz of PCS spectrum in markets where they already owned cellular licenses. Additionally, no carrier should have more than 45 MHz of total spectrum (cellular, PCS or Specialized Mobile Radios (SMR)) in a given market.

In May 1996, 493 BTAs licenses from Block C were awarded. The C Block auction was limited to entrepreneurs (companies owned by women and minority groups, as well as rural telephone companies).[6] In January 1997, the FCC completed the simultaneous D-E-F block auction. This auction attracted firms from Blocks A, B and C, seeking to increase their capacity, or to expand their services to different geographic areas (FCC (1997)). The F Block licenses were limited to entrepreneurs, who also won licenses in the D and E Blocks.

Broadband PCS systems operated in a digital format upon their inception. Besides TDMA and CDMA standards, some licensees installed Global System for Mobile Communications (GSM) network equipment. By 1996, eight PCS licensees had already inaugurated their service in portions of 29 MTAs.[7] Many other PCS licensees from Blocks A and B introduced their service during 1997.

While PCS licenses were allocated, Nextel Communications, the most important SMR provider, also entered digital mobile markets by providing services with iDEN technology (TDMA standard). By 1998, Nextel had entered 71 of the 100 largest cellular markets (Seim and Viard (2011)). Even though Nextel focused on business customers and it mainly used radio technology, the FCC treated this company as a mobile carrier similar to the PCS entrants (FCC (1998)). In this study I also include this company as a digital competitor.

[5] The FCC provides information about the correspondence between CMAs and BTAs.

[6] This "entrepreneurs" auction was designated to fulfill some social requirements stipulated by the Omnibus Budget Reconciliation Act of 1993. The FCC provided bidding credits and gave to entrepreneurs the chance to pay for their licenses in quarterly installments over a ten-year period at below market interest rates. Nevertheless, due to failure in the required down payments, some of the licenses had to be re-auctioned in July 1996.

[7] Sprint, Western Wireless, Bellsouth, Powertel, Pacific Bell, Primeco PCS, Omnipoint, and GTE Mobilnet (FCC (1997)).

As it can be observed, various incompatible standards and different frequency bands were used to provide digital service in the U.S. mobile market. I group all standards referring to them as digital technology given that the purpose of my research is not to study the importance of standardization, nor to distinguish the specific characteristics of each type of digital technology. To address my research question, among those digital carriers, I distinguish two types: 1) digital incumbents which were installed in an early stage and switched from analog to digital technology, and 2) digital entrants which began operations afterwards (PCS entrants and Nextel).

Competition and the presence of first-mover advantages: The dynamics of competition in the digital mobile market is influenced by the existence of first-mover advantages that put incumbents in a better position to compete against later entrants. There are several factors that generate those advantages. For example, on the demand side, buyer's switching costs are well recognized in the literature as an important source of early-mover advantages. Switching costs are commonly related to some initial investments that consumers have to make in adapting to firms' offers. Thus, late entrants must invest extra resources to attract customers away from the first-mover firm (Klemperer (1987)). In the context of this study, consumers had to buy a new phone when changing providers, even if they previously acquired a digital phone from cellular incumbents. This is because mobile operators used incompatible digital standards. Phones were only compatible with the digital network technology for which they were designed. A CDMA phone, for instance, was not able to work on a GSM network.

Furthermore, contractual costs associated to both signing long-term contracts and high termination fees also created switching costs. For instance, the FCC reports that this type of contracts were indeed offered together with subsidized-handsets, especially by cellular carriers, making it difficult for consumers to migrate to another company because their handset were tied to their contracts (FCC (1997)). Other forms of switching costs were associated with the cost people incurred when changing their mobile number (number portability was not implemented until 2003).[8] According to McLaughlin and LeDonne (2002), consumers that switched plans from analog to digital services keeping the same wireless carrier were able to keep their phone number, as long as they stayed within the same area code. Bijwaard et al. (2008) point out that the time and effort it takes to inform friends or business relations of a change in number deterred consumers from changing providers.

First-mover advantages are also related to brand recognition which is not necessarily spe-

[8]https://www.fcc.gov/wireless-local-number-portability

cific to network industries. Schmalensee (1982) studies how the uncertainty about the quality new firms offer may motivate consumers to contract from incumbents. An empirical study in Germany (Gerpott et al. (2001)) shows that brand-loyalty in mobile industry was associated with consumers' satisfaction when it comes to the quality of the service. They find that satisfied clients were less likely to change providers, even when entrants offered lower prices and good services.

Another source of early-mover advantages comes from the supply side. By the time that digital competitors come into play, incumbents may have covered some of their sunk cost, or possess a bigger consumer base that lowers the average costs (Schmalensee (1981)). Then, incumbent firms may price below its competitors further increasing its market share. Cellular incumbents had already installed cell towers to provide analog mobile services. Adding digital capabilities to an existing network generally involved minimal hardware additions at the base stations sites along with software upgrades in the mobile switching centers (Meyers (1997)). Frequently, incumbents did not require additional towers to provide digital service, which allowed them to avoid the difficulties associated with identifying new tower locations that the PCS entrants faced (Seim and Viard (2011)). Digital entrant, on the other hand, had to deal with more stringent regulation policies, and less availability of commercial areas to install antennas. The time of entry also generated an advantage for cellular operators in terms of coverage. Even though roaming agreements allowed firms to use other carriers' infrastructure, the high roaming fees demotivated consumers to contract service with firms with small coverage (FCC (1995)).[9]

There are also factors that creates advantages for late entrants in mobile markets. In particular, later entrants may obtain advantages by learning from incumbents' mistakes. Moreover, digital entrants may free ride on advertisement investments made by incumbents to make digital plans known to a large group of consumers. Finally, later movers can also benefit because technological or demand uncertainties may have decreased by the time of entry (Bijwaard et al. (2008)).

In summary, as described above, different forces come into play to explain the dynamics of competition in digital mobile markets. In this study, I use a two-type entry model to quantify the competitive advantage early movers have relative to later entrants. I measure the impact of competitors' entry on the profits of incumbents and entrants. It is important to note that this

[9] "Roaming" is the term that describes a wireless phone's ability to make and receive calls outside the home calling area under a particular service plan. Roaming occurs when a subscriber of one wireless service provider uses the facilities of a second provider. Roaming fees are typically charged on a per-minute basis and determined by your service provider.

study does not attempt to identify the source of first-mover advantages.

3.3 Data

This study investigates the competitive dynamics in the mobile industry using cross-sectional data of local markets in the United States. The data used in this study contain information on the number of digital incumbents and entrants (N_I, N_E). It also contains information on observable market characteristics that may affect firms' profitability in each local market. In this section, I first present the market definition. Next, I present the information on firms' entry per type. Finally, I present an overview of market characteristics.

3.3.1 Market definition

For the purpose of this study, I distinguish as many different local markets as possible, while defining markets such that firms compete with each other and that no firms outside the defined market are competitors. Therefore, for digital mobile markets, I define markets at the level of Basic Trading Areas (BTAs). I consider it more appropriate than city level market definition because it is closely related to the entry decision of PCS entrants. They cannot operate in a given market without a license, which guarantees that there is no relevant direct competition coming from outside the defined area. Although mobile licensees from neighbor BTAs could offer its services by using "home" carrier's infrastructure, customers usually preferred to contract service from a "home" carrier. This is because roaming fees were relatively higher in comparison to local calls, and only frequent travellers contracted this service (FCC (1995)). There are 493 local markets in total, I have information for 487 markets with an average population of 578,000.[10]

As previously mentioned, the FCC provided licenses to cellular digital incumbents at the level of Cellular Market Areas (CMAs). There is a total of 722 CMAs throughout the country. In order to match CMAs to BTAs, I use the FCC's mapping tables.[11]

[10]The following markets are excluded: B488 (San Juan, Puerto Rico), B489 (Mayaguez, Puerto Rico), B490 (Guam), B491 (U.S. Virgin Islands), B492 (American Samoa), and B493 (Northern Mariana Islands).

[11]http://wireless.fcc.gov/auctions/default.htm?job=maps

3.3.2 Digital mobile firms

I classify digital mobile firms into two types: incumbents and entrants. Incumbents refer to cellular operators that switched from analog to digital systems. Those that entered later (PCS licensees and Nextel) are classified as entrants. I do not consider as incumbent those cellular companies operating with analog technology, although I account for their presence as exogenous variable.

The total number of digital incumbents and entrants are obtained from two sources. The first one, shared by Seim and Viard (2011), contains detailed information about the number of digital incumbents and entrants for the largest 54 BTAs (in terms of population) in 1998. These local markets contain approximately 55% of total population. This information is collected from Kagan World Media's database. In the upper part of Table 3.1, I present counts of the observed market configuration for these markets. This table shows that there is no market in which incumbents exclusively provided digital mobile services. Additionally, the majority of markets have more than 3 entrants, and more than half of them have one incumbent.[12] Finally, in 13 markets no incumbent switched to digital technology before 1998.

The second source of information are 3 maps published by the FCC in its Third Annual Commercial Mobile Radio Services Competition Report (FCC (1998)). These maps present information about the deployment of digital technologies. One map shows the number of PCS operators in each of the 487 local markets. Another map provides partial information about the presence of digital incumbents. It only shows that at least one incumbent upgraded its systems to a digital one, but does not show the number of incumbents that actually switched their technology (it could be 1 or 2 firms in total). Finally, another map shows the deployment of Nextel's digital coverage.

The lower part of Table 3.1 shows counts of the observed market configuration constructed from these maps. From a total of 487 BTAs, 163 markets (33% of the total) are exclusively served by analog incumbent firms, and 53 (11%) have at least one digital incumbent but no entrants. From 271 markets with at least one digital entrant (56%), 50% have only 1 entrant, 26% have 2 entrants, and 24% 3 entrants or more.

[12] Only one market has 5 entrants, and 8 have 4 entrants. I grouped them in 3+ classification in order to facilitate the identification of my parameters.

Table 3.1: Number of digital incumbents and entrants per local market

A. Data from Kagan World Media's database

	Number of entrants			
Number of incumbents	1	2	3+	Total
0	1	4	8	13
1	5	8	18	31
2	2	1	7	10
Total	8	13	33	54

B. Data collected from the FCC's competition report

	Number of entrants				
Number of incumbents	0	1	2	3+	Total
0	163	82	26	18	289
1 or 2	53	54	45	46	198
Total	216	136	71	64	487

Note: This table presents counts of the different market configurations (N_I, N_E) observed in each BTA in 1998. *Source:* Kagan World Media and FCC's Third Annual Commercial Mobile Radio Services Competition Report.

3.3.3 Market characteristics

BTAs differ in their ability to generate the necessary demand to make digital firms' entry attractive. To account for these differences, I collect demand- and supply-side information about each local market. Market demographics come from the 2000 U.S. Census. Annual data is not available at the level of local markets, and I assume that annual changes in demographics are not large enough to considerably affect entry decisions (see Greenstein and Mazzeo (2006) for a similar assumption). The census data are at county level, so I convert the data (3,219 counties) to my market level definition using FCC's mapping tables.[13]

As in Bresnahan and Reiss (1991b), I use population as a *proxy* of market size. Table 3.2 shows that each market contains on average approximately 578,000 inhabitants. The demand for mobile service is expected to increase with the number of inhabitants. Nevertheless, Seim and Viard (2011) argue that population has an ambiguous effect on entry because it also makes it more difficult for firms to satisfy build-out requirements imposed by the FCC. The FCC

[13] http://wireless.fcc.gov/auctions/default.htm?job=cross_references

Table 3.2: Explanatory variables: summary statistics

Variable	Description	Mean	Std.Dev.	Min.	Max.
Population	Number of inhabitants (000s)	577.8	1,459.7	25.4	19,620
Per capita income	Per capita income (USD 000's)	17.5	2.8	8.5	31.2
Education	Average percentage of people with at least high school	77.9	7.4	42.6	92.7
Commute	Average commuting time (minutes)	23.0	3.9	12.9	36.7
WRI	Wharton Residential Urban Land Regulation Index	-0.2	0.7	-1.8	2.3
Land area	BTA land area (square miles)	7.3	19.4	0.3	343.2

Note: The table shows the demographic information I include as control variables in my model. Population size is presented in levels for expository purposes in this table. *Source:* U.S. Census (2000) and Gyourko et al. (2008).

imposed on every PCS licensee to serve between 25% to 33% of the market's population within 5 years.

Besides population, I include average per capita income (in thousands of U.S. dollars) and the level of education (average percentage of population with a high school degree or higher), both as measures of purchasing power. I also control for the average commuting time people used from their houses to work (in minutes). This variable is used as a *proxy* for the additional value of a mobile phone to frequent drivers (Seim and Viard (2011)), and it is expected to have positive sign on firms' profitability.

The FCC reports that the main difference in costs between incumbents and entrants is related to the installation of new antennas. Some communities became concerned about possible health effects from electromagnetic radiation and the aesthetics of the towers.[14] As a consequence, zoning regulations and other ordinances were increasingly used to limit or halt the construction of new towers. According to Seim and Viard (2011), firms required municipal approval in order to install new towers. Many local ordinances prohibited the installation of towers in residential areas, but allowed firms to place them in industrial and commercial areas. Hence, the strictness of local zoning laws affected the availability of tower sites in local markets, and thus increased firms' cost to build their network.

Similarly to Seim and Viard (2011), I include two variables to control for firms' difficulty to install antennas: size of BTA's land area, and a measure of regulatory stringency (WRI). Land area, measured in square miles, is a *proxy* of the availability of space firms had to deploy their network. This information is also provided by the 2000 U.S. Census, and I expect it to positively affect profits and entry.

The regulatory stringency measure is the 2005 Wharton Residential Urban Land Regulation

[14] An antenna is mounted in a building or a tower.

Index (WRI), created by Gyourko et al. (2008). This index is a survey-based, standardized measure of the stringency of residential growth-control policies. BTAs with a high WRI had zoning regulations that limit the growth of new residential areas, which may result in greater availability of candidate cell tower zones. This might ease market entry, so I expect this variable exhibits a positive effect on payoffs. This data is aggregated at the MSA level, I convert it to the BTA level by using correspondences provided by the census. In cases in which the correspondence is not clear, I assign to BTAs without information the average value per state.

I expect that the effect of both cost-side variables differ between incumbents and entrants. Incumbents, as first movers, have already found available cell tower sites to install their infrastructure. As previously mentioned, Meyers (1997) explains that cellular incumbents just needed to add digital capabilities to their towers, which involved minimal hardware additions.

3.4 Model

I use a static two-type entry model, assuming a free entry equilibrium condition,[15] and a strategic substitution among firms' entry choices. This model is inspired by Greenstein and Mazzeo (2006), who apply a similar approach to study competitive dynamics among regional and national competitive local exchange carriers in the United States. The structure of the entry game is based on Cleeren et al. (2010), as discussed in Subsection 3.4.1.

Structural entry models have been extensively studied after seminal works of Bresnahan and Reiss (1991b) and Berry (1992) were published. These models allow to make inferences about the nature of competition from observed market-specific characteristics and firms' entry choices (Bresnahan and Reiss (1991b)). It is assumed that firms choose to enter and stay in the market if they expect to earn positive profits *ex post*. Using a two-type entry model allows me to analyze the competitive dynamics between incumbents and entrants, and to measure their respective competitive strength. According to Greenstein and Mazzeo (2006), differentiation may determine the strength of *ex post* competition. Therefore, the distinction between types helps to explain the observed market structure accurately. Firms may also respond differently to similar economic conditions (demand- or cost-side factors).

There are important assumptions underlying this model. The first one is that firms' entry decisions are made on a market-by-market basis independently: this means that profits are economically independent across markets. This is a crucial abstraction, particularly when studying

[15] The allocation of spectrum allowed the entry to a maximum of six new PCS firms in a given local market. By 1998, all markets, except one, had less than 5 PCS carriers (FCC (1998)).

network industries because geographic complementarities might explain firms' entry choices. Fox and Bajari (2013) find empirical evidence of the existence of such complementarities in bidders' valuation functions for C block of the PCS spectrum band.[16] These complementarities arise when firms want to serve customers wishing to make calls while traveling. Other forms of complementarities include marketing and cost-of-service synergies. For example, in order to reduce interconnection costs, and the corresponding roaming fees, firms wanted to expand their network to adjacent markets. Nevertheless, there are many reasons to believe that this assumption does not represent a serious concern for the period used in this study. First of all, back then, mobile service was considered a local service. The FCC chose market boundaries to be in sparsely settled areas in order to minimize complementarities across markets. Moreover, 1900 MHz PCS wireless phone service was first deployed in urban areas and along major highways, so there might not even be PCS service along the boundaries of two markets. Finally, companies while using roaming agreements could provide their services in adjacent markets, however this practice was still very expensive and consumers were not willing to pay roaming surcharges (FCC (1997)). A consumers' guide published by the FCC in 2002 recommends consumers to be aware of the use of roaming services and their respective fee. According to this guide, firms' network was not fully deployed even inside local markets. Consumers were advised to research the various providers to determine the extent of their coverage in the areas that matter most to them. The guide also explains that roaming services are even used inside a local area: "if the handset's signal or the service provider's signal from the nearest antenna is too weak, roaming can occur automatically, even if you are using your phone in your own home calling area. A phone can also go into "roaming mode" if there is a high volume of calls in the area. For example, though you may be surrounded by sites from your provider, each of your provider's sites may be at its capacity or out of range. Instead of having a call blocked or dropped, your phone might use another provider's site (roam), sometimes at an additional cost to you." These recommendations show evidence that it took several years for firms to secure a national (or regional) coverage.

Another important assumption is made to solve the problem of multiple equilibria. The non-uniqueness of equilibria creates problems in identifying the parameters because the same underlying conditions can result in different observed outcomes. The literature of entry models show different solutions to deal with this multiplicity issue. I follow Cleeren et al. (2010) and

[16]However, many of C block winners did not enter the market and returned their licenses to the FCC due to financial problems. Other companies merged with larger firms or sold some of its licenses to other carriers. This suggests that the factors underlying bidder's valuation and firms' entry choices may differ. This study is based on information about the actual entry of mobile carriers.

assume that entry moves are made sequentially. A unique subgame perfect Nash equilibrium is thus found. This assumption is plausible for two reasons. First, the definition of types I use, incumbents and entrants, impose already a predetermined entry sequence. Given that incumbents (cellular providers) have entered the market first, I assume that they would also move first in the digital market, anticipating competitors' moves. Cellular incumbents already offered packages of analog mobile services. Adding digital capabilities to an existing network generally involved minimal hardware additions at the base station sites and software upgrades in the mobile switching centers. Depending on the design of incumbents' technological system, they did not even require additional cell sites for their transition (Meyers, 1997). Second, this assumption simplifies the estimation procedure because the corresponding likelihood function requires the estimation of rectangular areas of integration (see Figures 3.1 and 3.2 in Subsection 3.4.1).

3.4.1 Econometric framework

Digital mobile firms are defined as incumbents (I) and entrants (E) across each local market. The market structure is represented by an ordered pair (N_I, N_E) that indicates the number of observed firms per type. Firms play a two-period game: in the first period, they decide whether to enter or not to the market; in the second period, they compete and observe their level of profits. I assume that firms of the same type are identical, so they have the same profit function. However, I account for differences between types. Therefore, the level of costs, demand and the unobservables differ between incumbents and entrants. Latent profits per type $i = I, E$ in local market m, Π^i_m, are given by:

$$\Pi^i_m = \pi^i_m(N_I, N_E) - \varepsilon^i_m \tag{3.1}$$

where $\pi^i_m(N_I, N_E)$ denotes the deterministic part that depends on the number of both types of firms, and ε^i_m represents the components of firm's profits that are unobserved to the econometrician. This error term is assumed to be independent of the observable characteristics, and identical for each firm of the same type in a given market. Profits are normalized to zero for firms that do not enter the digital mobile market.

The competitive interaction among firms includes the interaction within and between types. First, I model the competitive interaction among the same type of firms assuming that their entry decisions are strategic substitutes. This means that an additional entrant of type i decreases the level of profits Π^i_m.

Assumption 1*: Entry decisions by firms of the same type are strategic substitutes*

$$\begin{aligned}\pi_m^I(N_I+1,N_E) &< \pi_m^I(N_I,N_E)\\ \pi_m^E(N_I,N_E+1) &< \pi_m^E(N_I,N_E)\end{aligned} \tag{3.2}$$

Second, I model the competitive interaction among different types of firms. I assume that incumbents and entrants' entry choices are strategic substitutes or independent (Equation 3.3).

Assumption 2*: Entry decisions by firms of different type are strategic substitutes or independent*

$$\begin{aligned}\pi_m^I(N_I,N_E+1) &\leq \pi_m^I(N_I,N_E)\\ \pi_m^E(N_I+1,N_E) &\leq \pi_m^E(N_I,N_E)\end{aligned} \tag{3.3}$$

If this condition holds with strict inequality, an additional entry of type E (I) negatively affects Π_m^I (Π_m^E). If Equation (3.3) holds with equality, firms are not affected by the entry of a different-type firm. This might happen if entrants focus on attending a different and new consumer segment.

Additionally, I assume that the competitive effect exerted by the same type of firms is stronger than the one exerted by firms of different type (Equation (3.4)). The belief behind this assumption is that the same type of firms target a similar consumer segment with similar marketing strategies. For example, the FCC reports that entrants tried to gain customers by solving the problems consumers faced with incumbent providers (e.g., no more long-term contracts). While incumbent firms took advantage of their size to motivate consumers be part of a larger network.

Assumption 3*: Entry decisions by firms of the same type have a greater impact than different-type firms*

$$\begin{aligned}\pi_m^I(N_I+1,N_E-1) &< \pi_m^I(N_I,N_E)\\ \pi_m^E(N_I-1,N_E+1) &< \pi_m^E(N_I,N_E)\end{aligned} \tag{3.4}$$

Assumptions 1, 2 and 3 are in line with previous empirical entry literature and together characterize the Nash equilibria of the game. The market configuration (n_I, n_E) is a Nash equilibrium outcome of the entry game if and only if the error terms satisfy the following conditions:

$$\begin{aligned}\pi_m^I(n_I+1,n_E) < \varepsilon_m^I \leq \pi_m^I(n_I,n_E)\\ \pi_m^E(n_I,n_E+1) < \varepsilon_m^E \leq \pi_m^E(n_I,n_E)\end{aligned} \tag{3.5}$$

When these conditions are satisfied, it is profitable for (n_I,n_E) firms to enter market m (i.e., $\Pi_m^I(n_I) \geq 0$, $\Pi_m^E(n_E) \geq 0$), but it is not the case for (n_I+1,n_E+1) firms (i.e., $\Pi_m^I(n_I+1) < 0$, $\Pi_m^E(n_E+1) < 0$). Assumption 1 guarantees the existence of such equilibrium.

As previously mentioned, (n_I,n_E) may not be a unique Nash equilibrium outcome. For some realizations of $(\varepsilon^I,\varepsilon^E)$, there may be multiple outcomes that, given Assumptions 1, 2, and 3, satisfy the conditions in Equations (3.5). Figure 3.1 illustrates one specific example where there are two potential entrants of each type. The bold lines delineate the areas of $(\varepsilon^I,\varepsilon^E)$ for which the market configuration (1,1), (0,2) and (2,0) are the Nash equilibria. It can be observed that there are areas in which (1,1) show multiplicity with (0,2) (shadow with horizontal lines), and areas in which it shows multiplicity with (2,0) (shadow with vertical lines). For some realizations of $(\varepsilon^I,\varepsilon^E)$, there are areas in which even the three outcomes are Nash equilibria.

Note that the area of multiplicity would disappear if firms of different types are independent, that is, if Assumption 2 holds with equality. For instance, if $\pi_m^I(1,2) = \pi_m^I(1,1)$, and $\pi_m^E(1,2) = \pi_m^E(0,2)$, the overlapping areas between (1,1) and (0,2) would disappear. As the degree of substitution increases, the multiplicity area also increases. Nevertheless, it will never be the case that both areas completely overlap. Given Assumption 3, the effect of different-type firms would never be as strong as the one exerted by the same-type firms. In Figure 3.1, $\pi_m^I(2,1)$ will always be lower than $\pi_m^I(1,2)$.

In general, under Assumptions 1, 2 and 3, the multiple Nash equilibria can be characterized by three claims.[17] If Assumption 2 holds with strict inequality:

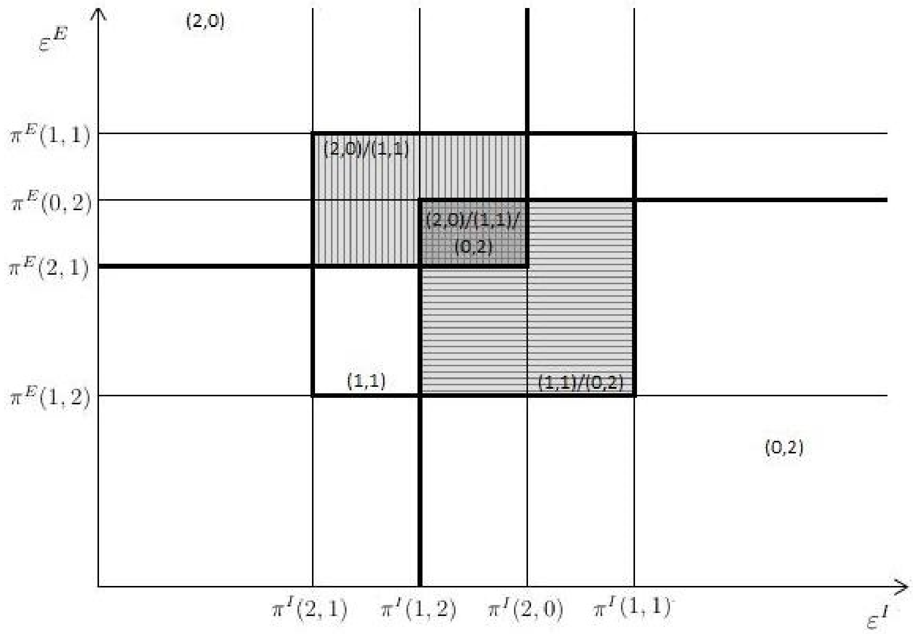
- ***Claim 1:*** (n_I,n_E) may only show multiplicity with Nash equilibrium outcomes of the form (n_I+k,n_E-k), where k is a positive or negative integer. In Figure 1, the outcome (1,1) show multiplicity with (2,0), or (0,2), but not, for example, with (1,0). There is a unique prediction of the total number of entrants, $n = n_I + n_E$.

- ***Claim 2:*** (n_I,n_E) necessarily shows multiplicity with (n_I+1,n_E-1) and (n_I-1,n_E+1).

- ***Claim 3:*** When (n_I,n_E) shows multiplicity with (n_I+k,n_E-k), the multiplicity area is necessarily a subset of the multiplicity area of (n_I+1,n_E-1) for $k>0$, and a subset of

[17] The complete proof of these claims is available in Cleeren et al. (2010).

Figure 3.1: Multiple Nash equilibria



Note: This figure illustrates an example of the multiplicity problem when there are two potential entrants of each type. The bold lines delineate the areas of $(\varepsilon^I, \varepsilon^E)$ for which the market configuration (1,1), (0,2) and (2,0) are the Nash equilibria. There are areas in which (1,1) show multiplicity with (0,2) (shadow with horizontal lines), and areas in which it shows multiplicity with (2,0) (shadow with vertical lines). For some realizations of $(\varepsilon^I, \varepsilon^E)$, there are areas in which the three outcomes are Nash equilibria.

the multiplicity area with $(n_I - 1, n_E + 1)$ for $k < 0$. In Figure 1, whenever $(2,0)$ show multiplicity with (0,2), the multiplicity area is a subset of the multiplicity area with $(1,1)$.

Together, these claims imply that the area for which (n_I, n_E) show multiplicity with any other Nash equilibrium is given by the areas of overlap with $(n_I + 1, n_E - 1)$ and $(n_I - 1, n_E + 1)$. The area of multiplicity with $(n_I + 1, n_E - 1)$ is defined by:

$$\begin{aligned} \pi_m^I(n_I+1, n_E) < \varepsilon_m^I \leq \pi_m^I(n_I+1, n_E-1), \\ \pi_m^E(n_I+1, n_E) < \varepsilon_m^E \leq \pi_m^E(n_I, n_E). \end{aligned} \tag{3.6}$$

Similarly, the area of multiplicity with $(n_I - 1, n_E + 1)$ is given by:

$$\begin{aligned}&\pi^I_m(n_I,n_E+1) < \varepsilon^I_m \leq \pi^I_m(n_I,n_E),\\&\pi^E_m(n_I,n_E+1) < \varepsilon^E_m \leq \pi^E_m(n_I-1,n_E+1).\end{aligned} \tag{3.7}$$

In order to obtain a unique prediction, I need to impose additional structure on the game. As already mentioned, I assume firms' entry decisions are taken sequentially. Specifically, I assume that incumbents are the ones who move first. I further use a refined equilibrium concept: subgame perfect Nash equilibrium. With this new structure, I am able to assign a unique outcome to every realization of $(\varepsilon^I,\varepsilon^E)$:

a) Whenever (n_I,n_E) and (n_I+k,n_E-k), with $k>0$, are both Nash equilibria, then (n_I+k,n_E-k) is chosen as the unique subgame perfect Nash equilibrium. Referring to Figure 3.1, when (1,1) and (2,0) are Nash equilibria, given that incumbents move first, the equilibrium (1,1) is not sustained. After one incumbent enters the market, the second incumbent prefers to enter before an entrant takes its place. Once two incumbents are present, no entrants enter and (2,0) is the unique solution.

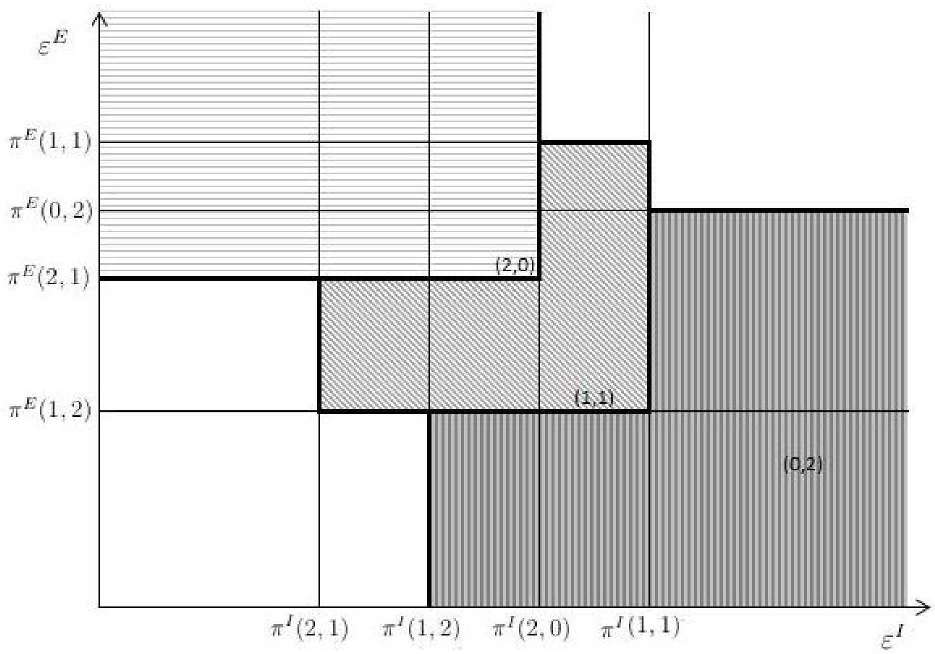
b) Whenever (n_I,n_E) and (n_I+k,n_E-k), with $k<0$, are both Nash equilibria, (n_I,n_E) will be the only subgame perfect Nash equilibrium. For instance, when (1,1) and (0,2) are Nash equilibria, (1,1) is chosen as equilibrium outcome.

In other words, the equilibrium with the largest number of incumbent firms is chosen as the only subgame perfect Nash equilibrium whenever multiple Nash equilibria exist. Figure 3.2 shows how multiple Nash equilibria become unique subgame perfect Nash equilibrium. To define the area where (n_I,n_E) is the subgame perfect Nash equilibrium, I subtract the area of multiplicity given by Equations (3.6) (n_I+1,n_E-1) from the area where (n_I,n_E) is a Nash equilibrium (as given by Equations (3.5)).

Assuming that $(\varepsilon^I,\varepsilon^E)$ has a bivariate standard normal distribution, I derive the probability of observing (n_I,n_E) in market m:

$$\begin{aligned}P(N_I=n_I,N_E=n_E) = &\int_{\pi^I_{(n_I+1,n_E)}}^{\pi^I_{(n_I,n_E)}}\int_{\pi^E_{(n_I,n_E+1)}}^{\pi^E_{(n_I,n_E)}}\phi(u_I,u_E)\mathrm{d}u_I\mathrm{d}u_E\\&-\int_{\pi^I_{(n_I+1,n_E)}}^{\pi^I_{(n_I+1,n_E-1)}}\int_{\pi^E_{(n_I+1,n_E)}}^{\pi^E_{(n_I,n_E)}}\phi(u_I,u_E)\mathrm{d}u_I\mathrm{d}u_E\end{aligned} \tag{3.8}$$

Figure 3.2: Subgame Perfect Nash equilibria



Note: This figure illustrates how multiple Nash equilibria become unique subgame perfect Nash equilibrium. Under the assumption that firms move sequentially and that digital incumbents move first, the equilibrium with the largest number of incumbent firms is chosen. For instance, when (1,1) and (0,2) are Nash equilibria, (1,1) is chosen as equilibrium outcome.

Where $\phi(.)$ denotes the density function of the standard bivariate normal distribution with a correlation parameter between ε^I and ε^E, ρ. Note that if firms of different types are assumed to be independents, it is not necessary to subtract the second term (there are no multiple Nash equilibria), and the model reduces to a bivariate ordered Probit model. If, in addition, I assume that ρ is equal to zero, the problem is reduced to two separate ordered Probit models, i.e., one-type entry model for each type.[18] As a first step towards the two-type entry model, I estimate a one-type entry model assuming that all firms are homogeneous. This will be used as preliminary evidence of strategic substitution among firms' entry decisions.

Once defined the probability of observing each market configuration, I construct the likelihood function to be maximized. Usually, the likelihood function for M local markets is defined

[18] For a detailed explanation about one-type entry model see Cleeren et al. (2006).

as:

$$L = \prod_{m=1}^{M} \text{Prob}(n_I, n_E)_m \tag{3.9}$$

Where $(n_I, n_E)_m$ is the observed configuration of firms in market m. Hence, if $(n_I, n_E) = (1,1)$ for market m, then the contribution to the likelihood function is Prob(1,1) (see Mazzeo (2002)). For this study, I have full information about the number of digital incumbents and entrants, (n_I, n_E), for 54 markets. However, for the remaining 433 markets, I do not have information regarding how many incumbents actually changed from analog to digital. In other words, the observed market configuration are either $(0, n_E)$ or $(1\,\text{or}\,2, n_E)$. My likelihood function is modified such that I combine both types of samples to identify my parameters.

3.4.2 Specification

The deterministic part of firms' profits is specified as a linear function of market level characteristics X, and observed entry choices of both types of firms in the market. I allow the effects associated with the variables in vector X to vary by type of firm. In addition, I model asymmetric competitive effects by including type-specific parameters to measure the impact of an additional entry of the same-type and different-type of firms (as in Schaumans and Verboven (2008), and Cleeren et al. (2010)):[19]

$$\begin{aligned} \pi^I &= X\beta_I - \alpha_I^{n_I} - \gamma_I^{n_E}, \\ \pi^E &= X\beta_E - \alpha_E^{n_E} - \gamma_E^{n_I}. \end{aligned} \tag{3.10}$$

The parameters $\alpha_i^{n_i}$ and $\gamma_i^{n_{-i}}$ are fixed effects measuring the competitive dynamics of the n-th same-type and different-type of firms, respectively. If, for instance, the difference between $\alpha_i^{n_i}$ and $\alpha_i^{n_i-1}$ is positive, then the entry of the last same-type firm has a negative impact on profits. This is interpreted as evidence of strategic substitution. Similarly, if the difference between $\gamma_i^{n_{-i}}$ and $\gamma_i^{n_{-i}-1}$ is positive, then the entry of a different-type firm negatively affects profits.

This specification allows me to quantify the advantage early movers have relative to later entrants. By estimating type-specific competitive effects, I can infer to what extent incumbent firms have a stronger competitive effect on entrant's payoffs. In the presence of first-mover advantages, it is expected that $(\gamma_I^{n_E} - \gamma_I^{n_E-1}) < (\gamma_E^{n_I} - \gamma_E^{n_I-1})$. This means that the entry of an

[19] In what follows, for expository convenience, the subscript m is dropped.

additional digital entrant has a lower competitive impact on incumbents' profits than vice versa. If no substantial difference is found then it means that incumbent firms do not possess first-mover advantages or that they have differentiated their products in such a way that they do not affect competitor's payoffs. In that case, the parameters γ_i^{n-i} are expected to be close to zero.

I use parametric assumptions to identify the parameters. I assume that the error terms follow a bivariate normal distribution, and restrict their standard deviation to be equal to one. Note that the competitive effects among firms of different types (γ_i^{n-i}) are identified through these parametric assumptions. As Schaumans and Verboven (2008) explain, conditional on observed market characteristics, the number of incumbents and entrants may be correlated because of substitution effects, γ_i^{n-i}, or because of unobserved market characteristics affecting both types' payoffs, captured through ρ. I can distinguish between both possibilities because the error terms are assumed to have a bivariate normal distribution. The scale of payoffs is not identified.

The estimated fixed effects, $\alpha_i^{n_i}$ and γ_i^{n-i}, should be increasing in order to keep the model internally consistent with Assumptions 1 and 2 (Schaumans and Verboven (2008), Cleeren et al. (2010)). To be consistent with Assumption 3, the difference between consecutive αs should be greater than the difference between consecutive γs.

Finally, these competitive effects are not all identified. The first same-type competitive effect is set equal to zero, $\alpha_i^0 = 0$.[20] Similarly, the first different-type competitive effect is normalized to zero, $\gamma_i^0 = 0$. As the constant term β_i^0 takes the value of zero for both types, all the rest of αs and γs should take a positive value. Maximum likelihood estimation selects parameters that maximize the loglikelihood of the observed market configurations across data.

3.5 Empirical results

This section presents the main results of the two-type entry model. Before showing these results, I first provide preliminary evidence on the competitive dynamics among digital firms assuming there is no distinction between incumbents and entrants. In other words, I estimate a one-type entry model (single ordered Probit model), where all firms are assumed to be homogeneous. Firms' entry decisions are assumed to be strategic substitutes (Assumption 1) as well.

Table 3.3 presents the parameter estimates of the one-type model. The estimated αs measure the impact of competition on firm performance. The results show there is a positive difference between α^{n+1} and α^n, which means that entry of an additional firm has a negative effect on

[20] The number of observed incumbents varies from 0 to 2, this means that $\alpha_I^0 = 0$. Similarly, the number of entrants goes from 0 to 3, therefore, $\alpha_E^0 = 0$.

Table 3.3: One-type entry model: digital firms

Parameter	**Estimate**	**Std. err.**
Effect on digital firms' payoffs		
Population	0.90***	(0.07)
Per capita income	0.08***	(0.03)
Commuting time	0.05***	(0.02)
Education	-0.01	(0.01)
WRI	0.26***	(0.08)
Dummy analog	-0.01***	(0.00)
Land area	-2.53	(0.15)
α^1	10.62***	(1.08)
α^2	11.70***	(1.10)
α^3	13.03***	(1.13)
α^4	14.12***	(1.15)
α^5	15.25***	(1.17)
N. observations		487
Log likelihood		-495.43

Note: This table reports the parameter estimates of the one-type entry model assuming all digital firms are homogeneous (there is no distinction between incumbents and entrants). The parameters are estimated by maximum likelihood. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

firms' payoffs. The results also indicate that population has a positive and significant effect (at 1% of significance level) on payoffs. Thus, markets with a large base of potential consumers make entry for digital firms more attractive. Per capita income and commuting time are also significant to explain entry choices: it pays more to enter markets where people have more purchasing power and spend more time commuting to work.

With respect to cost-side explanatory variables, I find evidence that additional entry is more attractive in markets where rolling-out infrastructure is less problematic (*WRI* is significant and has a positive coefficient). These results suggest that policy makers could motivate more entry by facilitating the construction of infrastructure through land-use regulations.

Table 3.4 presents the results for the two-type entry model as outlined in Section 3.4.[21]

[21] The dummy variable indicating the presence of analog firms is not included in this specification because it is highly correlated with the number of digital incumbents in the market.

Table 3.4: Two-type entry model: digital incumbents and digital entrants

	Estimate	Std. err.	Estimate	Std. err.
Effect on incumbents' payoffs				
Population	-0.28	(2.85)	0.56***	(0.18)
Per capita income			0.08	(0.08)
Commuting time			-0.05	(0.04)
Education			-0.05**	(0.02)
WRI			-0.05	(0.26)
Land area			0.00	(0.00)
α_I^1	2.11**	(1.01)	3.93***	(1.76)
α_I^2	2.43**	(1.02)	5.04***	(1.92)
γ_I^1	0.67	(2.27)	0.06	(0.41)
γ_I^2	2.06*	(1.06)	0.12	(0.43)
γ_I^3	3.05***	(1.05)	0.26	(0.55)
Effect on entrants' payoffs				
Population	0.47***	(0.11)	0.53***	(0.11)
Per capita income			0.07	(0.06)
Commuting time			-0.01	(0.03)
Education			-0.02***	(0.01)
WRI			0.13	(0.13)
Land area			0.00	(0.00)
α_E^1	5.30***	(1.05)	5.43***	(0.60)
α_E^2	6.29***	(1.04)	6.39***	(0.60)
α_E^3	7.07***	(1.02)	6.96***	(0.61)
γ_E^1	1.49	(1.08)	0.97***	(0.33)
γ_E^2	1.77	(1.46)	1.76***	(0.68)
ρ	0.01	(7.46)	0.93***	(0.07)
N. observations in sample 1	54		54	
N. observations in sample 2	433		433	
Log likelihood	-1091.1		-545.05	

Note: This table reports the parameter estimates of the two-type entry model. The parameters are estimated by maximum likelihood. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Two specifications are shown: the first only includes the fixed effects, αs and γs, to show that it is possible to identify them given the variation in my data. The second includes demand- and cost-side control variables. The results show that population remains significant to explain incumbents' and entrants' payoffs. Although not significant, *WRI* has a negative sign for incumbents and positive for entrants. The negative sign for incumbents suggests that entry to digital markets was more attractive where cell tower sites were less available. On the contrary, having available cell tower sites outside a residential area was key for entrants to deploy their network. This is due to the fact that incumbents have already installed antennas to serve the markets.

Concerning the competitive interaction among the same type of firms, the estimates are consistent with the assumption that firms' profitability is decreasing with the number of same-type firms (Assumption 1). This is shown by the estimated $\alpha_I^{n_I}$ and $\alpha_E^{n_E}$: they are increasing and significant at 1% of significance level in both cases. In other words, the entry of an additional incumbent reduces incumbents' profitability. Similarly, the entry of an additional digital entrant negatively affect entrants.

Concerning the strategic interaction between incumbents and entrants, the parameter estimates of $\gamma_I^{n_E}$ and $\gamma_E^{n_I}$ show an increasing pattern, which is in line with the assumption that entry decisions of different types of firms are strategic substitutes (Assumption 2). However, the results show that the competitive strength differs by type. For incumbent firms, the effect of an additional entrant to the market is negative but not significantly different from zero. On the contrary, the entry of an additional incumbent negatively affects the level of an entrant's payoffs. These results support the notion that incumbents posses first-mover advantages that allow them to have a stronger competitive effect on later rivals. Finally, the estimated parameters show that the entry effect of different types is less strong than the entry effect of the same type of firms (Assumption 3).

3.6 Conclusions

The introduction of digital technology is considered one of the most important innovations in the mobile industry because it allowed a more efficient use of the radio spectrum. In the United States, this disruptive innovation gradually displaced analog technology and allowed the entrance of new firms in the market.

In this context, and taking advantage of the definition of local mobile markets, I use a structural two-type entry model to empirically examine the competitive interaction among digital carriers. In particular, provided that first-mover advantages may determine the competitive dynamics, I compare the strength of competition of incumbent cellular operators with respect to the one of later entrants. I control for observed market-specific characteristics and unobserved determinants.

My results show the existence of strategic substitution among digital mobile firms. They also show that there is an asymmetric competitive strength in favor of incumbents. Specifically, my estimates indicate that incumbents exert a negative competitive impact on entrants' payoffs, but entrants do not affect incumbents' profitability. This asymmetry is in line with the presence of first-mover advantages in favor of incumbents.

In addition, my results have implications for policy makers who seek to promote effective competition into local mobile markets. It shows how important it is to recognize the asymmetries among operators to create a level-playing field between them. For example, policy makers could motivate more entry by facilitating the construction of infrastructure through land-use regulations. Another policy is to mitigate the larger competitive strength of incumbents by establishing asymmetric interconnection charges in favor of entrants. This shows that the allocation of new licenses is not enough to create more competition against incumbents. Regulatory and competition authorities should assure that those who enter the market at a later stage find adequate conditions to operate and compete against early rivals.

4 Patent Portfolio Choices: An Empirical Analysis of the U.S. Semiconductor Industry [1]

4.1 Introduction

Over the last decades, firms have rapidly expanded the size of their patent portfolios, especially in high-tech industries such as semiconductors.[2] In general, there has been a tremendous increase of granted patents. According to the U.S. Patent and Trademark Office (USPTO), patent grants from U.S. companies have grown by 50% from 1994 to 2004, and by 72% from 2004 to 2014. In a recent paper, Choi and Gerlach (2017) argue that the recent explosion of patent applications and patent portfolio acquisitions, as well as the increase of related litigations, demand a new paradigm of patent analysis that shifts away from isolated patents toward patent portfolios.

Understanding how firms decide on their patent portfolio is key to analyzing market competition: firms' R&D choices may ultimately define how they compete in the market (Choi and Gerlach (2017)). Patents can be used as a mechanism of exclusion when firms accumulate patents and this induces a competitor to reduce its investments in new products. Moreover, firms analyze market competition conditions regularly and respond to the changes by adjusting their portfolio choices, therefore moving their future R&D effort towards the most profitable technologies. For instance, in 2016 Qualcomm Inc., one of the leading firms in the semiconductor

[1]Financial support from Qualcomm Inc. is gratefully acknowledged. The research on which this paper is based was conducted in accordance with the rules set out in the Royal Dutch Academy of Sciences (KNAW) Declaration of Scientific Independence.

[2]Semiconductors are essential components that control all modern electronics, such as the sensors in car tires and medical monitors, massive cloud-based computer systems and reconnaissance satellites.

industry, announced that it will invest in the automotive industry. With an extensive patent portfolio of cellular communications, Qualcomm is a leading supplier to the mobile industry. It seems that Qualcomm's change of strategy in investing in the automotive industry may be due to the smartphone market showing signs of maturing. Therefore, the company seems to be looking for a more diversified portfolio. For this reason, Qualcomm has recently acquired NXP, a Dutch semiconductor company, given its position in the automotive chip-market and its connections with big auto-makers. In addition, this acquisition should drastically improve Qualcomm's position in the "Internet of Things"[3] by using NXP's portfolio (Pressman (2016)). This shows that, in promoting competition, policy makers need to take into account that firms respond strategically to changes in the market by introducing new patents.

Even though there has been a drastic rise in the size of firms' patent portfolios, existing empirical research on how firms choose where to position themselves in the technological market is scant. Several empirical studies on R&D investment take a firm's technological choice as exogenous. This paper aims to shed new light on how firms decide where to position their patent portfolios. In particular, I endogenize firms' technological choices across different classes of technology and relate them to the portfolio choices of other firms. To this end, I use data on firms' patent portfolios from the U.S. semiconductor industry from 1978 to 2002. The U.S. semiconductor industry provides an excellent setting within which to examine firms' portfolio choices, given the rapid pace of technological change and the complexity of firms' technologies that make firms heavily interrelated. Considering that firms of different size may dispose of different financial resources and may react differently to the competitive dynamics, I estimate the model by distinguishing firms according to their size (in terms of number of employees): small, medium, large, and giants. My model measures how the choices of each type of firm relate to their previous choices. Considering the importance that giants have in the market, I complement these results by empirically analyzing whether firms that locate their portfolios far from giants are more likely to produce patents. For this last analysis, I use a co-agglomeration measure that allows me to characterize the position of each firm in relation to giants' portfolio.

Most existing research has focused on firms' strategy with respect to the size of their portfolio (total number of patents), largely ignoring the composition of portfolios. For instance, Hall and Ziedonis (2001) conduct an empirical analysis of patenting behavior in the U.S. semiconductor industry between 1979 and 1995. They analyze the link between the pro-patent shift in

[3]The Internet of Things has been defined in Recommendation ITU-T Y.2060 (06/2012) as a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.

the U.S. legal environment, through the creation of the Court of Appeals for the Federal Circuit (CAFC) in the 1980's, and the strategic response of firms.[4] They find that capital-intensive firms invested aggressively in patents after this pro-patent policy change. Capital-intensive firms engage in patent portfolio races to reduce concerns about being held up by external patent owners and to negotiate access to external technologies on more favorable terms. Aligned with Hall and Ziedonis (2001), Ziedonis (2004) finds that firms use an aggressive patenting strategy when rights to complementary patents are widely distributed among outside entities, as it is the case in the semiconductor industry. The central argument is that having technologies that draw upon a more disparate set of owners makes infeasible other *ex ante* forms of contracting, such as joint ventures or patent pools. This is primarily due to the costs and delays associated with these forms of contracting. Not being able to use *ex ante* mechanisms increases the strategic value of patenting for use in *ex post* licensing transactions.[5]

A few theoretical models have analyzed patent portfolios as a whole rather than individual patents. Choi and Gerlach (2017) analyze how the size of patent portfolios affects litigation incentives and how this feeds into incentives to develop new products. In particular, they show that "patent peace[6]" is more likely to arise when product market competition is weak, and patent portfolios are either sufficiently small or sufficiently large. If portfolios are small, firms lack offensive litigation capacity while when they are sufficiently large, there is a strong potential for counter-litigation. They also show that as the competitiveness of the industry intensifies, the relative gains from excluding a rival through litigation are higher. Therefore, as one firm accumulates patents, a rival firm's incentives to develop a new product decreases.

Parchomovsky and Wagner (2005) also develop a patent portfolio theory emphasizing that the true value of patents lies not in their individual worth, but in their aggregation into a patent portfolio. They argue that patent portfolios are not simply singular items, but rather a strategic collection of related-but-distinct individual patents that, when combined, confer an array of important advantages upon the portfolio holder. They argue that the amassment of patent portfolios generates "scale" and "diversity". Scale allows the freedom to innovate, avoiding costly litigation, improving bargaining position and holders' ability to attract and retain capital investment. Moreover, the scale-features of patent portfolios enhance the ability to consolidate and coordinate related technological developments within the holding firm. Diversity, on the other hand, allows firms to hedge against the risk and uncertainty related to future market conditions

[4] See Section 4.2 for more information about this policy shift in the U.S. legal environment.
[5] Schankerman and Noel (2013) find similar results for the U.S. computer software industry.
[6] "Patent peace" refers to the opposite of patent litigation.

or future competitors.

In addition, Parchomovsky and Wagner (2005) distinguish the differences between small and large firms' patenting strategies. For large firms, a major driver is the need to create substantial "patent portfolios—independent of the expected values of any particular individual patents." Small firms, however, are likely to be substantially more resource constrained, and thus may prefer to invest in the higher-risk strategy of selectively seeking "important" patents within a technical field. Another strategy followed by upstart innovators is to combine their inventions with firms that have a larger portfolio, rather than seeking to develop their own niche in the market.

My findings suggest that firms differ in their technological choice and decide where to invest depending on their size. In particular, I find that small firms invest in technologies where large firms have previously invested. Large firms' choices, on the other hand, are not affected by the previous technological choices of small firms. There could be two possible explanations for this finding. One is that small firms face more uncertainty than larger firms and prefer to follow large market players assuming they choose to invest in profitable technologies. Another explanation is in line with Hall and Ziedonis (2001) who show that firms in the semiconductor industry increase their size of portfolio to gain bargaining power. Therefore, small firms put more effort in those technological fields where they must compete with larger players. A third explanation may be in line with Parchomovsky and Wagner (2005)' theory that argues that small firms combine their R&D efforts with large firms. Similarly, medium-size firms' choices are positively related to large firms' previous technological choices. In other words, medium-size firms find it more profitable to follow large firms' portfolio choices. Moreover, the choices of medium-size firms show persistence with respect to the actions taken by their own type in the previous period. In the case of large firms, the choice of investing in a particular technology is positively related to the number of medium, large and giants that have previously invested in the same technology. The fact that large firms' choices are (weakly) related to giants' portfolio choices could be related to their investment capacity that allows them to hold a similar portfolio as giants'. Finally, giants' choices are only positively related to their previous choices. To complement these results, I analyze how the technological decision of small, medium and large-firms in relation to giants affect their future performance in terms of number of patents. My findings suggest that firms that chose in the past a portfolio less similar to giants' portfolio do not have a larger number of patents. This means that the ones that diversified their portfolio in different fields have not invested in more patents than the ones that decided to follow giants more closely.

The remainder of the paper is organized in the following way. Section 4.2 describes the U.S. semiconductor industry. Section 4.3 gives a detailed account of the data. Section 4.4 presents my descriptive analysis of patent portfolio choices, including the empirical framework and results. Section 4.5 concludes with policy recommendations.

4.2 The U.S. semiconductor industry

The U.S. semiconductor industry provides an excellent setting within which to examine firms' portfolio choices given its rapid pace of technological change. The number of patents of U.S. semiconductor firms has risen considerably during the last decades. Figure 4.1 shows the evolution of the total number of granted patents from 1978 to 2002. For example, in 1990, 1,870 patents were granted to U.S. companies, while in 2002 the number of granted patents increased to more than 11,000. This growth put the U.S. semiconductor companies in top positions as patent recipients. Before 1996, only one firm, Texas Instruments, appeared in the list of the top fifteen U.S. corporate patent recipients. As of 1996, Intel, AMD and Micron Technology joined Texas Instruments in this list. According to the latest report published by the Semiconductor Industry Association (SIA (2015)),[7] five of the top fifteen U.S. corporate patent recipients in 2015 were U.S. semiconductor companies. This high ranking can be explained by the fact that U.S. semiconductor companies collectively invest roughly one-fifth of total sales annually into R&D, the highest share of any industry.

The growth in the number of U.S. patent applications accelerated drastically since the 1980's when important changes in the U.S. legal environment strengthened the rights granted to patent holders (Hall and Ziedonis (2001), Schankerman and Noel (2013)). The most important legal change occurred in 1982 with the formation of the Court of Appeals for the Federal Circuit (CAFC). This court unified the judicial treatment of patent rights in the United States. In general, this court transformed the legal environment from one that was generally skeptical of patents to one that promoted the broad, exclusive rights of patent owners. The Court was also more willing to grant preliminary injunctions to patentees during infringement suits, and to sustain large damage awards (Merges (1997)). Hall and Ziedonis (2001) show that the surge in patenting by semiconductor firms is causally related to the pro-patent shift in the U.S. legal environment, especially for firms with large sunk costs in complex manufacturing facilities.

The shift to a pro-patent legal environment involved a gradual process. Because of various

[7] The Semiconductor Industry Association is formed by leading companies such as AMD, IBM, Intel, Micron Technology, Qualcomm, among others.

Figure 4.1: U.S. patents granted to U.S. semiconductor firms

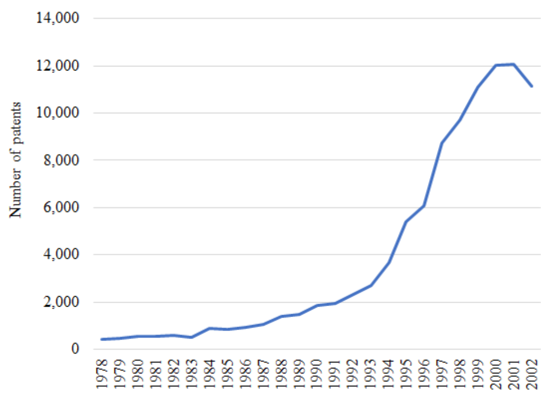
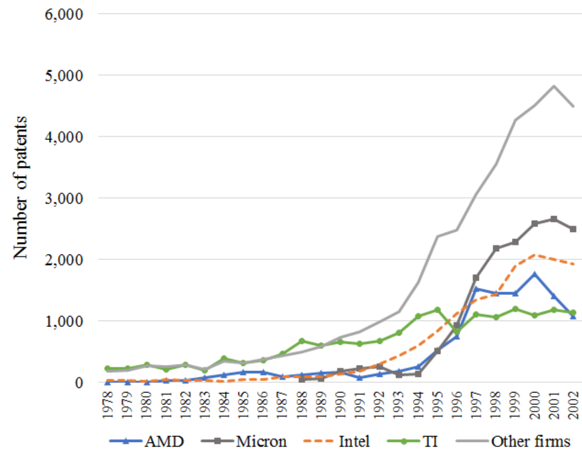


Figure 4.2: U.S. patents granted to U.S. giants in semiconductor industry



Note: Figure 4.1 and Figure 4.2 show the number of patents per application year. *Source*: NBER.

lawsuits between 1983 and 1986,[8] firms were concerned about the possibility of being shut down with an injunction, which could generate high losses. Firms also realized that lacking a strong patent portfolio with which to negotiate licensing or cross-licensing agreements could be translated into a more rapid erosion of profits. In the 1990s, the rapid growth in patenting is explained by a series of judicial decisions concerning the patentability of software.[9] For example, in 1994, an important change occurred when the CAFC expanded the scope of software patents, allowing companies to apply for more patents.

The semiconductor industry also provides an excellent setting to examine how firms strategically decide where to position themselves in the technological space. Firms typically invest in “complex" technologies where innovation is cumulative and requires numerous separate patents (Choi and Gerlach (2017)). This means that any new product or process is likely to overlap with technologies previously developed by other firms. Therefore, firms need to consider the patent holder when they decide which class of technology they will invest in. Among all patent holders, there are a few giants that hold a significantly larger portfolio compared to other firms in the market. Between 1988 and 2002, there were 4 firms that together held 60% of the total

[8]Two important cases are identified as pivotal in reshaping firms’ patent strategies: the Kodak-Polaroid case in 1986, and the patent infringement suits of Texas Instruments during 1985-1986 (Hall and Ziedonis (2001)).

[9]Many semiconductor firms hold patents in software (see Subsection 4.4.1 for more information).

number of patents: AMD, Intel Corp, Micron Technology and Texas Instruments.[10] By the end of 2002, each of them held a portfolio of more than 10,000 patents. Figure 4.2 shows that among them, the firms that grew the most in the last years are Intel and Micron Technology. Both firms invest in memory technologies and a breakdown of their portfolio choices shows that they are the ones that have a larger distance in the technology space. In Section 4.4, I describe in more detail firms' patent portfolio choices across different classes of technologies, as well as the relationship between technological distance and patent portfolio size.

4.3 Data

This section presents two types of data. First, I use data on patents collected from the National Bureau of Economic Research (NBER) database. Patents have been shown to provide a useful measure of a firm's intangible stock of knowledge. Nevertheless, they have limitations that not all patents meet the U.S. Patent and Trademark Office (USPTO) criteria for patentability, and that not all inventors seek to patent Forman et al. (2016). Second, I use data on firms' characteristics from Compustat database. My analysis is based on 156 publicly traded U.S.-owned firms whose principal line of business is in semiconductors and related devices (SIC 3674)[11] between 1978 and 2002. To this group of firms I add 7 publicly traded U.S. firms that were identified by Hall and Ziedonis (2001) as important market players in the semiconductor industry, but were classified with a different SIC code.[12] My sample is selected such that all firms have patented at least once since 1978, and each of these firms have data on Compustat for at least 3 consecutive years. This leaves an unbalanced panel of a total of 163 firms between 1978 and 2002.

The NBER data archive contains detailed information on more than 3 million U.S. patents granted between 1976 and 2006 by the USPTO. Although the NBER database contains information on patents granted until 2006, my empirical analysis includes patents with application dates from 1978 (the first year when there were more than 20 firms) to 2002. Similarly to Forman et al. (2016), I also cut off the last four years of the data to avoid right truncation issues related to lags between year granted and year filed. Due to the delay between application and issuance dates, I count patents using the year of application. In this way, I follow more closely

[10] According to the SIA's report, these 4 firms continue leading the U.S. semiconductor industry in 2015.

[11] Standard Industrial Classification. SIC codes are assigned to each company according to its primary business activity (as determined by revenue).

[12] Hall and Ziedonis (2001) identified those firms using ICE Status Reports (1976-1998).

firms' R&D decisions over time. The NBER database matches patent assignees to firms, which makes it easy to identify which firm applied for the patent. Patents could be assigned to the inventor or a firm' subsidiary and the USPTO does not keep a consistent identifier for the same patenting entity from year to year. One drawback, however, is that the match between assignees and firms is based on the 1989 universe of companies. Given that I do not have data on mergers and acquisitions that took place between 1990 and 2002, I therefore have not included in my analysis the changes in patents' ownership as if 1990.[13]

To analyze firms' choices on R&D across different technologies, I rely on the examiners' allocation of patents to classify patents into different classes of technology. In particular, I use the 4-digit International Patent Classification (IPC) code to measure how firms choose technology. While the patent class indicates the nature of the invention (e.g., software), it does not indicate the way the invention is used (e.g., automotive or computer systems). However, IPC classification has been widely used in research to characterize firms' locations in technological or knowledge space, as well as the proximities among firms. For instance, Bloom et al. (2013) and Schankerman and Noel (2013) use it to measure technological spillovers among firms. Benner and Waldfogel (2008) use it to calculate the technological distance between Kodak and Canon from 1980 to 2000. The IPC system had its origin in the Council of Europe's 1954 "European Convention on the International Classification of Patents for Invention." The classification has been managed by an international agency since 1969. Since that year, U.S. patents have been classified according to both the U.S. and IPC schemes. Given that each patent can be classified into more than one IPC code to correctly capture firms' technological scope, I count each different 4-digit IPC code as a separate patent. In other words, a patent is double-counted if it belongs to two different classes of technology.[14] According to Benner and Waldfogel (2008), research often has employed only the first listed patent classification in measures of firms' technological proximities. However, counting single patent class generate imprecise measures of technology proximity among firms.

Patents are classified through a careful process.[15] Whenever a firm applies for a patent at the USPTO, an examiner reviews the incoming patent application and assigns it to one of the U.S. patent subclasses (more than 100,000). This classification determines which examining group

[13]This means that if, say, firm A was granted a patent in 1985 and it was acquired by firm B in 1988, then the NBER registers firm B as the patent holder. On the other hand, if firm A was acquired after 1989, then firm A appears as the patent holder.

[14]On average, there are 1.1 IPC classes per patent over the entire sample period. This means that the increase in the number of patents is not due to an increase in the number of IPC classes over time.

[15]See Benner and Waldfogel (2008) for a more detailed explanation of this process.

reviews the application. A specialized examiner in the assigned group then evaluates the application. To assess its originality, the examiner searches previous patents issued in the original and related subclasses, as well as on-line databases. At the same time that the examiner assigns the patent to U.S. patent subclasses, he also assigns it to one or more IPC subclasses. The examiner classifies these patents carefully because he uses these classifications in his searches of the prior technologies. To maintain the quality of the classification and its consistency across examining groups, another examiner reviews the classification of all issuing patents.

I use the IPC classification for three main reasons. First, according to Benner and Waldfogel (2008), the IPC schemes appear to have better quality compared to the U.S. classification. The World Intellectual Property Organization (WIPO) performs periodic reviews to the IPC classification. Although the USPTO carefully assigns patents into the proper international subclasses, it devotes limited attention to the arrangement of the U.S. subclasses. Second, the IPC scheme reflects the economic importance of new inventions because it focuses primarily on industry and profession, while the U.S. scheme focuses on technical aspects. Finally, the first four levels of the IPC classifications are nested, while the U.S. system uses subsets not necessarily nested. For example, 435/40 is a subset of 435/39, but 435/41 is not a subclass of any of these (USPTO, 1993).

Besides patent data, I use firm level accounting data collected from Compustat. More specifically, I use information on the level of R&D investment and the number of employees. Both variables are known determinants of firms' patenting decisions. Given that firms may choose their technologies taking into account their respective capacities and/or bargaining power, I classify firms into four categories according to their size (in terms of number of employees) to analyze their patent portfolio choices. Small-type firms have less than 200 employees during the entire sample period.[16] Medium-type firms are those with more than 200 but less than 2,000 employees.[17] Large-type firms contain more than 2,000 employees, but I exclude the four giants (AMD, Intel, Micron Technology and Texas Instruments) and analyze their portfolio separately because of their unique portfolio size (more than 10,000 patents each).

Table 4.1 summarizes firms' characteristics and portfolio choices per type of firm from 1978 to 2002. For instance, there are 40 small firms that, on average, have 100 employees and invest 43 millions (1987) dollars on R&D per year. This R&D investment represents 22% of the total amount of sales per year. Concerning their patent portfolio choices, small firms together hold

[16] This means that the maximum number of employees is lower than 200 (first quartile of the distribution) from 1978 to 2002.

[17] Second and third quartile of the distribution.

Table 4.1: Firms' and patent portfolios' characteristics per type of firm (1978-2002)

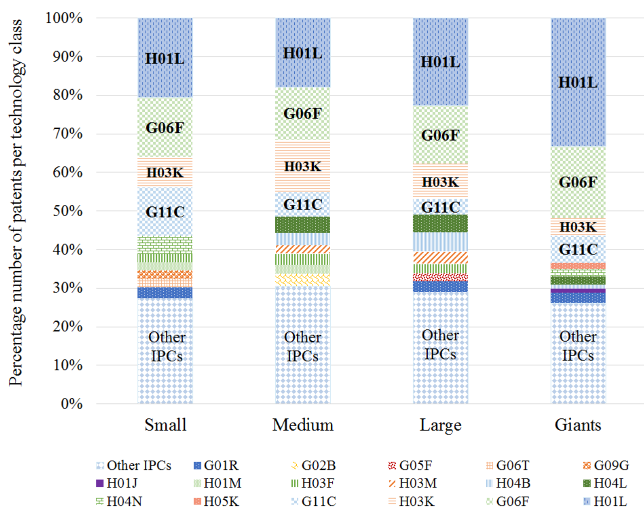
	Total	Small	Medium	Large	Giants
Number of firms	163	40	79	40	4
Firms' characteristics					
average number of employees per year	3,162	100	495	4,144	31,283
average R&D investment per year (millions of 1987 dollars)	680	43	214	921	6,901
average sales per year (millions of 1987 dollars)	4,847	193	1,083	5,766	52,045
R&D/Sales (%)	14%	22%	20%	16%	13%
Portfolios' size					
total number of granted patents	97,534	1,413	8,652	27,945	59,524
average number of granted patents per firm	598	35	110	699	14,881
number of granted patent over R&D (millions of 1987 dollars)	0.88	0.83	0.51	0.76	2.16
Portfolios' composition					
total number of IPC	515	111	199	300	413
average number of IPCs per firm	23	7	14	36	232
Average $\tilde{HHI}$ (based on the number of patentes per IPC)	2,716	3,165	2,833	2,120	1,976

Note: This table summarizes the characteristics and patent portfolios of 163 U.S. semiconductor firms from 1978 to 2002. The Herfindahl-Hirschman Index (HHI) describes the concentration of patents across patent classes. Since HHI is biased upward when the number of patents is small, I use the adjusted HHI measure proposed by Hall (2005), $\tilde{HHI}$, to correct for this bias. Then, $\tilde{HHI} = \frac{(N \cdot HHI)-1}{N-1} \cdot 10,000$, where $HHI = \sum_{\tau}(\frac{N_\tau}{N})^2$, and N_τ is the number of patents in technology class τ.

1,413 patents and their patent propensity, measured by the number of patents per million of R&D investment, is larger than medium- and large-size firms. Concerning the composition of firms' portfolios, small firms' portfolios are composed of 7 different classes of technologies on average (they together invest in 111 different classes). To show firms' portfolio concentration in terms of the number of classes of technologies, I calculate the Herfindahl-Hirschman Index ($\tilde{HHI}$) using the share of patents per IPC class for each firm.[18] Small firms have on average a higher level of concentration per technology class. This means that they focus their R&D investment in fewer technology classes compared to other types of firms. From this table, one can also notice the importance of giants in the industry. These four firms together hold 59,524 and each of them has a portfolio with more than 232 IPC classes. They also have more than 30,000 employees and invest more than 6,900 million (1987) dollars per year, which represents 13% of their sales. The next subsection presents an analysis of patent portfolio choices in more detail.

[18] The Herfindahl-Hirschman Index is biased upward when the number of patents is small. I use the correction proposed by Hall (2005) to correct for this bias (see Table 4.1).

Figure 4.3: Composition of patent portfolio per type of firm



Top 10 IPC	Small	Medium	Large	Giants
G01R	3%		3%	3%
G02B		4%		
G05F			2%	
G06F	15%	15%	15%	19%
G06T	2%			
G09G	2%			
G11C	13%	5%	4%	7%
H01J				1%
H01L	21%	23%	23%	33%
H01M	2%	2%		
H03F	2%	3%	2%	
H03K	8%	9%	9%	5%
H03M		2%	3%	
H04B		3%	5%	1%
H04L		5%	5%	2%
H04N	5%			2%
H05K				2%
Subtotal	73%	71%	71%	74%
Rest	27%	29%	29%	26%

4.4 Empirical analysis

The following empirical analysis includes two subsections. In the first one, I endogenize patent portfolio choices and analyze how firms of different size differ in their patenting strategies. In the second subsection, I analyze how firms' patenting behavior of small, medium and large firms is related to their technological distance with respect to giants. In both cases, the analysis is composed by a general description, followed by a simple regression and its results.

4.4.1 Firm "location" across technological markets

This subsection describes the composition of firms' patent portfolio based on the information collected from the NBER database for the period 1978 to 2002. As previously mentioned, given that firms may choose their technologies taking into account their respective capacities and/or bargaining power, I analyze the composition of patent portfolios grouping firms by their size. I define four categories according to their number of employees: small (S, <200 employees), medium (M, 200-2,000 employees), large (L, >2,000 employees) or giants (G,>2,000 employees and >10,000 patents). The giants are the four most important patent holders of the industry: AMD, Intel, Micron Technology and Texas Instruments.

Figure 4.3 shows the composition of patent portfolios. IPC stands for International Patent Classification and this figure shows the 10 most important classes of technology for each type.[19]

[19] An empty space in the table means that a particular class is not part of the top ten list of IPC classes for that

Giants hold 33% of their patents in H01L class (semiconductor devices and electric solid state devices). Further, giants' second most important technology class (19%) is G06F (electric digital data processing). According to Schankerman and Noel (2013), class G06F is mainly used for software patents. Classes H01L and G06F are also the most important for small, medium and large-size firms; however, their portfolios are less concentrated in both classes (H01L (22%) and G06F (15%) approximately) as compared to giants. This may be related to the fact that non-giants prefer to focus on different technologies in order not to compete with giants. Therefore, small, medium and large firms show a greater diversification in their portfolios. For example, small firms have 13% of their patents in class G11C (semiconductor devices for static storage) and 8% in class H03K (pulse technique used in electronic circuits), while medium and large-size firms have 9% of their patents in class H03K.

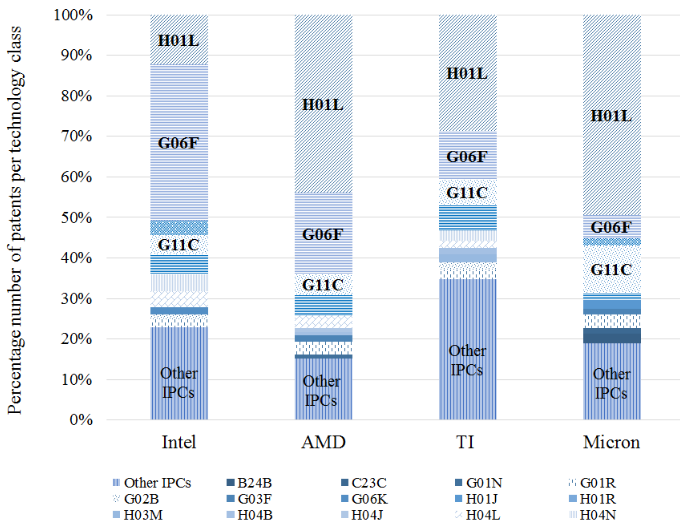
Furthermore, this table shows that different patent classes appear within the top ten classes of technology per type of firm. In the case of small firms, the technology classes G06T (image data processing) and G09G (control arrangement or circuits) are among their top ten choices while none of them are part of the top ten ranking for the other types of firms. Similarly, medium-size firms invest in class G02B (optical elements), while large firms do so in class G05F (systems for regulating electric or magnetic variables). This indicates that firms follow different patenting strategies. Nevertheless, they still coincide in certain fields. Medium and large-size firms coincide in all but two classes of technology. Giants and large firms follow with 7 classes, while the rest coincide in a maximum of 6 classes. These technological choices will be further analyzed in Subsection 4.4.1. Finally, besides the differences in portfolios' composition, Table 4.3 shows that all types of firms have more than 70% of their patents in these 10 classes of technology (out of 515 classes in total).

I group firms' portfolios to better show the technological choices made by firms of different size. However, one should keep in mind that there is also variation in portfolios' composition within types of firms. As previously shown in Table 4.1, on average, small firms have patents in 7 technology classes, while medium and large firms have patents in 14 and 36 IPC classes, respectively. Giants have patents in more than 200 IPC classes on average. In other words, not all the firms invest in the same IPC classes. Also, small firms have a less diversified portfolio ($\tilde{HHI}$ = 3,165) than medium-size firms ($\tilde{HHI}$ = 2,833), large firms ($\tilde{HHI}$ = 2,120) and giants ($\tilde{HHI}$ = 1,976).[20]

type of firms.

[20] The Herfindahl-Hirschman index is corrected by the total number of patents per firm following Hall (2005) (see Table 4.1).

Figure 4.4: Composition of patent portfolio for giants



Top 10 IPC	Intel	AMD	TI	Micron
B24B				2%
C23C				1%
G01N		1%		
G01R	2%	3%	2%	3%
G02B	1%		2%	
G03F		2%		1%
G06F	39%	20%	12%	6%
G06K	2%			
G11C	5%	5%	6%	12%
H01J				2%
H01L	12%	44%	29%	49%
H01R				
H03K	5%	5%	6%	2%
H03M			2%	
H04B		1%	2%	
H04J		1%		
H04L	4%	3%	2%	
H04N	4%		2%	
H05K	4%			2%
Subtotal	77%	85%	65%	81%
Rest	23%	15%	35%	19%

Given the importance of giants in this industry, I further analyze how Intel, AMD, Texas Instrument and Micron Technology develop their patent portfolios. Figure 4.4 shows that AMD and Micron have the highest level of portfolios' concentration. They invest 81% and 85% of their total patent portfolios in the top ten IPC. Intel and Texas Instrument follow with a total of 71% and 65%. Although most of the firms have patents in two main classes (H01L and G06F), their distribution among these two differ. For example, Intel holds 39% in G06F and 12% in H01L, while Micron Technology holds 49% in H01L and 6% in G06F. Among the giants, these two firms have clearly positioned their R&D efforts across technologies in a different manner and, as previously shown in Figure 4.2, they show the largest growth from 1994 to 2002. In the next subsection, I further analyze the relationship between technological choices among the different types of firms. In Subsection 4.4.2, I elaborate on the relationship between technological distance and innovation.

Firms' choice of patent portfolios

To widen the understanding on firms' portfolio choices per type of firm, this section provides empirical evidence on how technological choices of different types relate to each other in the U.S. semiconductor industry. Benner and Waldfogel (2008) point out that it is better to characterize firms' locations in technological space by aggregating patents of different years and using all listed patent classes on a patent, rather than just the first one. For this reason, I analyze firms' portfolio in a period of 5-years (instead of using yearly data), hence also considering the

Table 4.2: Technological choices and observable characteristics at IPC level

Dependent variable: technological choices (IPC level)				
	Small	**Medium**	**Large**	**Giants**
$d^j_{1998-2002}$=1	61	137	236	329
$d^j_{1998-2002}$=0	454	378	279	186
Total # IPCs	515	515	515	515

Explanatory variables (IPC level)				
	Mean	**Std. Dev.**	**Min.**	**Max.**
$N^S_{1993-97}$	0.27	1.2	0	15
$N^M_{1993-97}$	0.95	3.4	0	33
$N^L_{1993-97}$	1.27	3.1	0	22
$N^G_{1993-97}$	1.00	1.3	0	4
$\text{Pat}_{1993-97}$	51.62	419.1	0	7,124
Number of observations (IPCs)				515

Note: This table shows summary statistics of the variables used to estimate Equation (4.1). I estimate this equation for each type of firm. *Source*: NBER.

time firms may need to develop new technologies and apply for patents. Given that firms have patented more intensively during the last years (see Table 4.5 in Appendix A), I focus on the last 5-year period of my sample 1998-2002.

I define a binary outcome per type in which d^j_τ takes the value of 1 if any firm of type j= small (S), medium (M), large (L) or giant (G) applies for a patent in technology τ during the period 1998-2002. d^j_τ takes the value of zero if no firm of type j applies for a patent in technology τ during this 5-year period:

$$d^j_\tau = \begin{cases} 0 & \text{if at least one firm of type j have patents in technology class } \tau, \\ 1 & \text{if no firm of type j have patents in technology class } \tau. \end{cases}$$

Table 4.2 shows counts of these choices for all classes of technology (IPC level). For example, out of 515 classes of technology, from 1998 to 2002 small firms have patented in 61 different classes. Giants hold patents in 329 classes of technologies in the same period. Patent portfolios' composition depends on observable and unobservable factors that influence firms' technological choices. I assume that there is an underlying latent variable that is modeled as a linear function of the observed technological choices of all types of firms. Consequently, technological choices depend on the number of same-type firms investing in technology τ (N_{τ}^{j}) and different-type firms that also invest in the same class of technology (N_{τ}^{-j}). As a *proxy* of the technological opportunity of each class, or in other words, how attractive the class is, I use the total number of patents (Pat_{τ}). To partially control for endogeneity problems caused by unobserved shocks that drive firms to invest in the same technology class, I use the lag of both variables. In other words, I use the patent information from the previous 5 years (1993-1997).[21]

Finally, the error term is added and it represents those variables that influence firms' choices and are unobserved to the econometrician, but common to all firms of the same type per class of technology. This implies that firms of the same type are treated as homogeneous. For expository reasons, in what follows, I drop the subscript τ. The subscripts p_1 and p_2 denote both time periods: 1993-1997 and 1998-2002, respectively.

To estimate this model, I assume that unobserved factors (ε^{j}) follow a standard normal distribution function. Therefore, the likelihood contributions are:

$$\Pr(d_{p_2}^{j} = 1 | N_{p_1}^{j}, N_{p_1}^{-j}, Pat_{p_1}) = \Phi(\beta^{j} N_{p_1}^{j} + \delta^{j} N_{p_1}^{-j} + \gamma^{j} Pat_{p_1}), \tag{4.1}$$

where Φ is the cumulative distribution function for the standard normal distribution. From these probabilities, I construct the likelihood function (probit model), and estimate the parameters by maximum likelihood.

My findings show that each type of firm reacts differently to the actions taken by other types of firms. For example, Table 4.3 shows that small firms invest in technologies where large firms have invested in the previous period. This suggests that small firms mainly follow large firms' actions when deciding where to focus their R&D efforts on. There could be three possible explanations for this finding. One is that small firms face more uncertainty than larger

[21] The underlying assumption is that firms respond rapidly to technological changes in this industry. Therefore, patenting activities of the last 5 years are important to explain todays' firms technological choices, but the choices made 10 years ago do not determine the new technological path. However, it is true that patents last for 20 years. Therefore, the presence of some firms that patented more than 10 years ago might still deter some type of firms to invest in certain technological markets. Also, most technological changes are incremental, i.e., firms base their new technology on previous developments. Finally, this model does not account for endogenity problems that may be generated if unobserved shocks that drive firms to invest in certain technology are serially correlated. To solve these issues, further research needs to be done.

Table 4.3: Type j's choices across technologies

	Small firms	**Medium firms**	**Large firms**	**Giants**
$N^{S}_{p_1}$	0.057	0.501	-0.176	0.150
	(0.12)	(0.31)	(0.32)	(0.10)
$N^{M}_{p_1}$	-0.035	0.749***	0.552**	-0.108
	(0.07)	(0.16)	(0.17)	(0.07)
$N^{L}_{p_1}$	0.293***	0.344***	0.613***	0.083
	(0.06)	(0.07)	(0.10)	(0.05)
$N^{G}_{p_1}$	0.077	0.128	0.106*	0.258*
	(0.08)	(0.07)	(0.05)	(0.12)
# patents$_{p_1}$	-0.003	-0.002	0.000	0.099**
	(0.00)	(0.00)	(0.00)	(0.04)
N. observations	515	515	515	515
Log Likelihood	-110.13	-166.56	-259.04	-280.33

Note: The dependent variable is a binary outcome per type in which d^{j}_{τ} takes the value of 1 if any firm of type j= small (S), medium (M), large (L) or giant (G) applies for a patent in technology τ during the period 1998-2002. d^{j}_{τ} takes the value of zero if any firm of type j does not apply for a patent in technology τ during this 5-year period. Each column shows the determinants of technology choices for firms of different size. The parameters are estimated by maximum likelihood. Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

firms whether their investment would be profitable. Then smaller firms prefer to learn from large market players and therefore follow them. Another explanation is in line with Hall and Ziedonis (2001) who show that firms in the semiconductor industry increase the size of their portfolio to gain bargaining power. Therefore, small firms put more effort in those fields where they must deal with larger players, in this way they can level their position in the market. Another explanation is in line with Parchomovsky and Wagner (2005) who argue that small firms are likely to combine their R&D effort with larger firms, rather than seeking to develop their own niche in the market. Similarly, medium-size firms' choices are positively related to large firms' previous technological choices. Moreover, their choices show persistence with respect to the actions taken by their own type in the previous period.

For large firms, the choice of investing in a particular technology is positively related to the number of medium, large and giants. This positive relationship might indicate that large firms diversify more to hedge from the risk of depending on a particular technology, as argued by Parchomovsky and Wagner (2005). Finally, giants do not follow other types' choices, while they are positively related to their previous investments and the total number of patents.[22]

4.4.2 Co-agglomeration and innovation

Based on the growth of patents of Micron Technology and Intel, and the differences in their patent portfolios' composition (see 4.4.1), in this section, I analyze in more detail how differences in technological choices relate to patenting behavior. To measure technological distance among firms, I first estimate a measure based on firms' distribution of patents across different classes of technology (IPC classes). Then, I estimate a patent equation that regress the total number of patents per firm and their respective technological distance.

I use a co-agglomeration measure created by Ellison and Glaeser (1997) to study firms' location choices in the same geographic areas.[23] In the context of technological areas, the co-agglomeration index EG_i is defined as:

$$EG_i \equiv \frac{\sum_{\tau}(T_{i\tau} - x_{\tau})^2}{1 - \sum_{\tau} x_{\tau}^2}, \tag{4.2}$$

where $T_{i\tau}$ is the proportion of all firm i patents in technology class τ and x_{τ} is the share of total patents in the technology class τ. If the distribution of patents across technologies are the same for all the firms, then this index takes the value of zero (firms co-agglomerate). The more firms differentiate from other firms' R&D choices, the larger the value this index takes. A large value may indicate that firms do not choose co-agglomeration as their preferred R&D strategy.

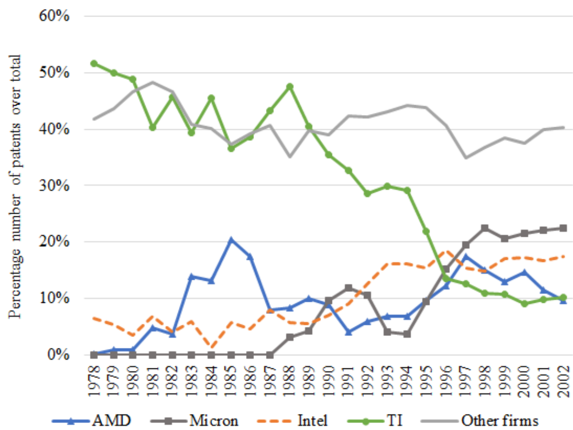
Figure 4.5 shows the evolution of the percentage number of patents held by giants from 1978 to 2002. One can observe that AMD, Micron Technology and Intel grew faster than Texas Instruments during the 1990s. In particular, Micron Technology and Intel Corp became the leaders in terms of patent portfolio size. Next to this figure, in Figure 4.6, I show the co-agglomeration index calculated for 3 periods of 5 years: 1988-1992, 1993-1997, and 1998-2002.[24] It can be

[22] Appendix B shows the coefficient estimates when I also include the percentage number of patents per technology over the total portfolio for small, medium, large and giants. I use this as a *proxy* of how present each type of firm is in each class of technology. These variables are generally not significant, probably due to its correlation with the number of firms. The results of this specification also show that small and medium-size firms mainly follow large firms. In addition, medium-size firms follow giants. Moreover, I find that the probability of investing in certain technology is positive related to the percentage of patents for small and large firms. Similarly, giants follow their previous technological choices. They seem to invest in markets where medium-size firms are not present.

[23] Bloom et al. (2013) also use this index to calculate technological distance between pairs of firms and estimate spillover effects.

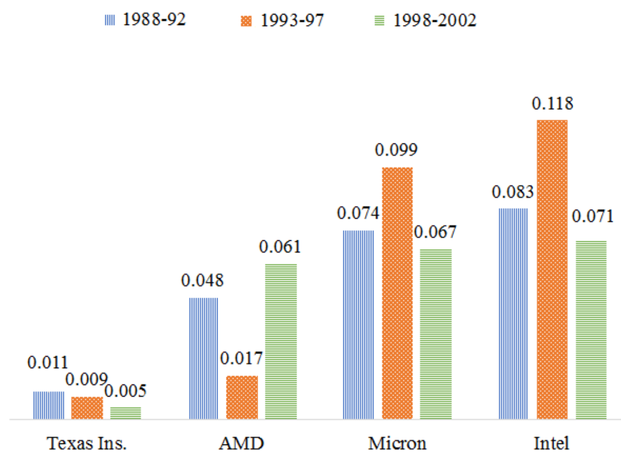
[24] Although Micron Technology was founded in 1978, this firm started to patent in the late 1980s.

Figure 4.5: Percentage number of patents over total: Giants



Note: This figure presents the percentage of number of patents over the total number per application year.

Figure 4.6: Co-agglomeration index per period: Giants



Note: This figure shows the Ellison-Glaeser agglomeration measure per firm for three different periods.

observed that both Intel and Micron Technology are the ones that co-agglomerate less. In other words, their R&D choices are such that their patents distribute across technologies differently than the average. These results indicate that Micron Technology and Intel grew the most by choosing two different technological locations apart from what other firms in the industry have chosen.

Since my interest is to evaluate technological strategies for small, medium and large-size firms as well, I model a patent production function per firm to estimate the effect of co-agglomeration for these types of firms. The exact specification is further explained in the next subsection. Given that giants are the most important market players these firms may have to deal with, I use instead as a measure of co-agglomeration the distance firms have with respect to giants' portfolio. In other words, I include the following co-agglomeration measure in the estimation of the patent production function:

$$EG_i \equiv \frac{\sum_{\tau}(T_{i\tau} - x_{G\tau})^2}{1 - \sum_{\tau} x_{G\tau}^2}, \tag{4.3}$$

where $x_{G\tau}$ is the share of total patents giants have in the technology class τ. This measure allows me to focus on strategies followed by non-giants with respect to the most important patent holders.

Patent Equation

To explore whether small, medium and large-size firms patent more or less when they distance from giants' portfolio choices, I estimate a patent production function that relates the number of successful patent applications made by a firm i in a given period p (Pat_{ip}) to its respective co-agglomeration index (EG_{ip}).[25] As previously mentioned, this index measures how different firms distribute their patents across various classes of technology. I consider periods of 5 years to better characterize firms' technological location. In addition, I employ the lag of this variable, EG_{ip-1}, to control for reverse causality.[26] This means that I measure whether firms that have positioned themselves farther away from giants in the previous period patent more or less than firms that chose to co-agglomerate. Because the number of successful patent applications made by a semiconductor firm is a count variable with many zeros, I use a Negative Binomial model:

$$E[\text{Pat}_{ip}|X_{ip}] = \exp(\lambda_1 \ln \text{R\&D}_{ip} + \lambda_2 \ln \text{EG}_{ip-1} + \lambda_3 \ln \text{Pat}_{i\,p-1} + \lambda_3 \text{S}_i + \lambda_4 \text{M}_i + \lambda_5 \text{L}_i + \eta_p + \nu_{ip}) \tag{4.4}$$

Besides the co-agglomeration index, I include other firm characteristics that drive firms' patenting activities, such as R&D investment ($R\&D_{ip-1}$) and size (Hall and Ziedonis (2001) and Bloom et al. (2013)). Size is measured by dummy variables, S_i, M_i, and L_i, where they take the value of 1 depending on firms' size. For example, S_i takes the value of 1 when a firm is classified as small and 0 otherwise. The same logic applies for M_i and L_i for medium and large firms, respectively. I include period fixed effects, η_p, to control for those factor that affect patenting strategies of all firms over the period. Finally, I include a lagged dependent variable to control for persistence in patenting behavior ($\ln \text{Pat}_{p-1}$). This variable also allows me to control for size effects in EG_{ip-1}. In other words, given firms' portfolio size, I measure how the variation in portfolios' composition affects innovation. I estimate this model by maximum likelihood.

Based on the estimation of the patent equation in (4.4), Table 4.4 shows that there is a

[25] This measure is specified in Equation 4.3.

[26] Firms with bigger patent portfolios are more likely to have an index closer to zero because they invest in more technology fields than small firms. Therefore, a spurious negative relationship is driven by the way this index is constructed.

Table 4.4: Coefficient estimates for the patent production function

Variables	Parameter
$\ln \text{Pat}_{ip-1}$	0.46***
	(0.08)
$\ln \text{R\&D}_{ip-1}$	0.14*
	(0.06)
$\ln \text{EG}_{ip-1}$	-0.06
	(0.13)
M_i	0.65***
	(0.16)
L_i	1.47***
	(0.24)
η_{p_2}	1.01***
	(0.25)
η_{p_3}	1.07***
	(0.24)
η_{p_4}	1.29***
	(0.21)
η_{p_5}	1.52***
	(0.25)
N. observations	277
Log Likelihood	-1,382.5

Note: Dependent variable is the number of patents per firm per period. Estimation is conducted using the Negative Binomial model. Standard errors (in parenthesis) allow for serial correlation through clustering by firm. A dummy variable is included for observations where lagged number of patent equals zero or where lagged R&D investment equals zero. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

negative but no significant effect of the co-agglomeration index (EG_{ip-1}) on the number of patents. The negative sign is aligned with a defensive patenting strategy where firms closer to giants increase the size of their portfolio to gain bargaining power. Since it is not significant, this suggests that not all the firms follow this defensive strategy. In addition, this result differs from the positive relation I found between the growth of Micron Technology and Intel and their choice of holding a more distant patent portfolio, suggesting that different forces drive small, medium, and large-size firms patenting strategies.

Furthermore, in line with previous research, the results also show that there is strong persistence in patenting behavior, i.e., the number of patents in the previous period is positive and significant. Concerning size, as one could expect, I find that medium and large firms patent more than small firms. Finally, I find that high R&D firms are more likely to produce patents.

4.5 Conclusions

Over the last few decades, patents have become increasingly important in the way firms do business and compete in the market. Firms react strategically to changes in market conditions by shaping their patent portfolios. This explains the rise of patent applications, patent acquisitions, as well as patent litigations. To understand firms' strategic choice on patent portfolio, this paper contributes to the literature by empirically analyzing how firms of different size choose their technologies in relation to other firms. To this end, I use data from the U.S. semiconductor industry from 1978 to 2002. This industry provides an ideal setting given firms' rapid technological change and the complexity of their technologies. Furthermore, similarly to other high-tech industries, the U.S. semiconductor industry is characterized by the presence of a few giants that hold the vast majority of patents. Therefore, understanding how firms react to their presence is key for policy makers to promote competition.

In my first descriptive analysis, I endogenize patent portfolio choices and analyze how firms of different sizes differ in their patenting strategies. The results show that small-, medium-, large-size firms and giants follow different patenting strategies. In particular, I find that small- and medium-size firms mainly follow large firms but not giants. In addition, the relationship between the technological choice of large firms and giants is positive and weakly significant. Taking into consideration these different strategies may help policy makers when promoting innovation. For instance, promoting innovation in fields where giants are positioned would not necessarily benefit small firms.

Considering the importance that giants have in the market, in my second analysis, I empirically analyze whether firms that locate their portfolios far from giants are more likely to produce patents. For this model, I use a co-agglomeration measure that allows me to characterize the position of each firm in relation to giants' portfolio. By estimating a patent production function, I find that there is a negative but no significant effect of the co-agglomeration index on the number of patents. The negative sign is aligned with a defensive patenting strategy where firms closer to giants increase the size of their portfolios to gain bargaining power. A non significant effect suggests that not all the firms follow this defensive strategy. Further research is needed to better understand the relationship between firms' technological location (composition) and size.

This research presents a new descriptive analysis of firms' portfolio choices. However, various issues are left for future research. In first place, there might be some unobserved forces that influence both the size of the firm and their patenting activity. This can create endogeneity problems that may be biasing my estimates. Secondly, technological choices are also related to the firms' position in the product market. Two firms that closely compete downstream may prefer two different technological locations. Finally, the type of business of a firm may determine its patenting strategy. For instance, fabless chip makers may seek to develop new technologies faster than manufacturers.

Appendix A

Table 4.5: Patent portfolios' characteristics per period and firms' size

	Small	Medium	Large	Giants
Portfolios' size				
total # patents (1978-2002)	**1,413**	**8,652**	**27,945**	**59,524**
period (1978-1982)	44	266	573	1,401
period (1983-1987)	46	589	845	2,531
period (1988-1992)	245	1,158	2,164	5,388
period (1993-1997)	536	2,135	7,930	15,901
period (1998-2002)	542	4,504	16,433	34,303
Portfolios' composition				
total # IPC (1978-2002)	**111**	**199**	**300**	**413**
period (1978-1982)	28	58	71	117
period (1983-1987)	22	69	70	129
period (1988-1992)	31	75	107	184
period (1993-1997)	58	110	172	247
period (1998-2002)	61	137	236	329

Note: This table shows the total number of patents and the number of IPC classes per period and firms' size. *Source*: NBER.

Appendix B

Table 4.6: Probit model: determinants of portfolio choices

	Small firms		Medium-size firms		Large firms		Giants	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$N^S_{p_1}$	0.057	-0.447	0.501	0.488	-0.176	-0.119	0.150	0.258
	(0.12)	(0.26)	(0.31)	(0.38)	(0.32)	(0.46)	(0.10)	(0.25)
$N^M_{p_1}$	-0.035	-0.051	0.749***	0.544*	0.552**	0.559	-0.108	-0.328**
	(0.07)	(0.09)	(0.16)	(0.24)	(0.17)	(0.33)	(0.07)	(0.10)
$N^L_{p_1}$	0.293***	0.292***	0.344***	0.295**	0.613***	0.199	0.083	0.150*
	(0.06)	(0.07)	(0.07)	(0.10)	(0.10)	(0.20)	(0.05)	(0.06)
$N^G_{p_1}$	0.077	0.066	0.128	0.137*	0.106*	0.106	0.258*	0.286*
	(0.08)	(0.09)	(0.07)	(0.07)	(0.05)	(0.05)	(0.12)	(0.14)
# patents$_{p_1}$	-0.003	-0.011	-0.002	-0.001	0.000	0.001	0.099**	0.100
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)
perc. patents$^S_{p_1}$		1.124*		0.088		-0.406		-0.395
		(0.56)		(0.68)		(0.97)		(0.24)
perc. patents$^M_{p_1}$		0.103		3.100		0.942		1.447*
		(0.22)		(2.69)		(4.44)		(0.65)
perc. patents$^L_{p_1}$		0.212		0.936		20.324*		-0.322
		(0.66)		(1.74)		(9.47)		(0.32)
perc. patents$^G_{p_1}$		2.476		-0.21		-0.213		-0.899
		(2.08)		(1.01)		(0.36)		(13.71)
N. observations	515	515	515	515	515	515	515	515
Log Likelihood	-110.1	-103.4	-166.6	-165.6	-259.0	-253.8	-280.3	-274.4

Note: Dependent variable is the choice to invest in a technology class. Each column shows the determinants of technology choices for firms of different size: small, medium, large and giants. The parameters are estimated by maximum likelihood. Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

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