Spillover effects and city development*

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Abstract

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 paper 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. Building on this result, I further analyze the potential effect of different public policies, such as strategically granted tax reliefs or redistributive schemes, on the ultimate market structure. The results show that taking into account this asymmetry is relevant for both new entrant firms and policy makers.

JEL classifications: L10, O18, R0.
Keywords: spillover effects, entry, urban policies.

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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. 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)

[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.

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 (1991), 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 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 2 describes the data. Section 3 presents the baseline model and provides preliminary evidence on spillover effects. Section 4 describes the full two-type model and estimation strategy. Section 5 discusses the results of the model and Section 6 presents the results of counterfactual simulations. Section 7 concludes with a brief summary of the main findings.

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

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.

2.1 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]

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.

[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 ensure the exclusion of highly dense urban areas.

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 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 ("Broodjeszaken"), 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), night-clubs, 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

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

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 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.

2.3 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 shows, each market in my sample contains on average approximately 4,600 residents, of which a large percentage 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 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 presents the average per capita revenues of cafeterias and

Table 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.

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.

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 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 3.1 and jump directly to the discussion of results in Section 3.2.

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

Table 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.

activity, ruling out purely residential areas (see Section 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:

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

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:

$$\ln r(N) = X\lambda + \alpha^{N} + \frac{\delta^{N_j}}{N} + \xi. \tag{2}$$

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.

$$\ln\tfrac{\mu(N)}{f} = X\varphi + \tau^{N} + \rho^{N_j} - \eta. \tag{3}$$

Substituting both equations (2 and 3) in the profit equation, the entry condition (1) is written as

$$X\beta + \ln S + \theta^{N+1} + \gamma^{N_j} < \omega < X\beta + \ln S + \theta^{N} + \gamma^{N_j}, \tag{4}$$

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 $\xi = \ln r - X\beta - \alpha^N - \frac{\delta^{N_j}}{N}$. 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.

3.2 Preliminary evidence

Table 4 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 (1991)).

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 pat-

Table 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.

tern, 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 4 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.

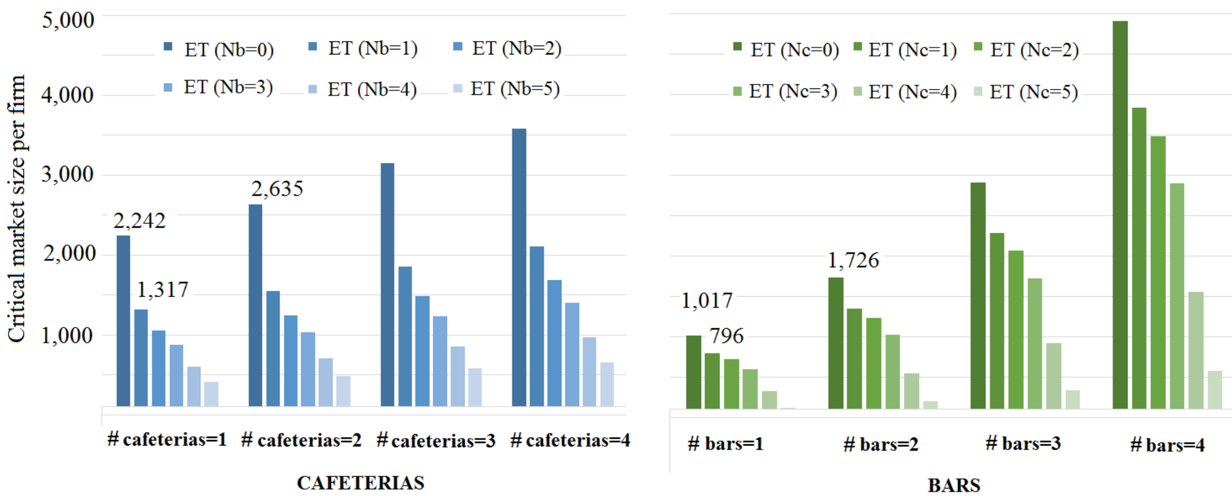
Entry thresholds per firm: To provide further insights into the estimated magnitude of spillover effects, and to produce a benchmark for the full model, I compute the entry thresholds per firm based on the parameter estimates, $S(\hat{N})/N$. Entry thresholds, $S(N)$, are defined as the critical market sizes (population) required to profitably support a certain number of cafeterias (bars), for a given number of bars (cafeterias). Using equation (4) for a representative average market ($\omega = 0$ and $X = \bar{X}$), the entry threshold to support N, given N_j is defined by

$$\hat{S}(N) = \exp(-\bar{X}\hat{\beta} - \hat{\theta}^N - \hat{\gamma}^{N_j}). \tag{5}$$

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 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 7).

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

Figure 1: Preliminary evidence on spillover effects



Note: Estimated entry thresholds per firm (see Equation 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.

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 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 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.

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.

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

$$\Pi_i(N_C, N_B) = \mu_i(N_C, N_B)\, r_i(N_C, N_B)\, S - f_i \tag{6}$$

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

[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.

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*

$$\begin{aligned} \pi_C(N_C+1, N_B) &< \pi_C(N_C, N_B) \\ \pi_B(N_C, N_B+1) &< \pi_B(N_C, N_B) \end{aligned} \tag{7}$$

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 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*

$$\begin{aligned} \pi_C(N_C, N_B) &\leq \pi_C(N_C, N_B+1) \\ \pi_B(N_C, N_B) &\leq \pi_B(N_C+1, N_B) \end{aligned} \tag{8}$$

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 (1991), Mazzeo (2002), Greenstein and Mazzeo (2006)), I assume that the effect of entry of an other-type firm is lower than the

[11] The exact specification will be explained in subsection 4.3.

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

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*

$$\begin{aligned} \pi_C(N_C+1, N_B+1) < \pi_C(N_C, N_B) \\ \pi_B(N_C+1, N_B+1) < \pi_B(N_C, N_B) \end{aligned} \tag{9}$$

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 4.4.

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

$$\begin{aligned} \pi_C(n_C+1, n_B) < \omega_C \leq \pi_C(n_C, n_B) \\ \pi_B(n_C, n_B+1) < \omega_B \leq \pi_B(n_C, n_B). \end{aligned} \tag{10}$$

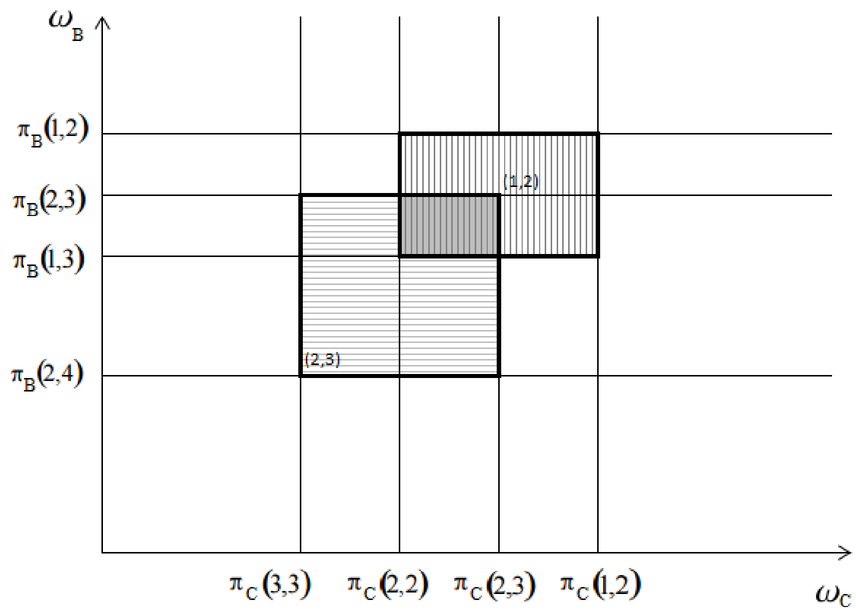
When these conditions are satisfied, it is profitable for n_C cafeterias and n_B bars to enter $(\Pi_i(n_C, n_B) \geq 0)$, but any additional bar or cafeteria will not have an incentive to do so. Assumption 1 guarantees that there are realizations of ω for which (10) holds, so that the market configuration (n_C, n_B) is observed with positive probability.

Equivalently, replacing the profit equations (6) in (10) and taking logs,

$$\begin{aligned} \ln \frac{\mu_C(n_C+1, n_B)}{f_C} + \ln r_C(n_C+1, n_B) + \ln S < 0 < \ln \frac{\mu_C(n_C, n_B)}{f_C} + \ln r_C(n_C, n_B) + \ln S \\ \ln \frac{\mu_B(n_C, n_B+1)}{f_B} + \ln r_B(n_C, n_B+1) + \ln S < 0 < \ln \frac{\mu_B(n_C, n_B)}{f_B} + \ln r_B(n_C, n_B) + \ln S. \end{aligned} \tag{11}$$

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). 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 $\pi_B(1,3) = \pi_B(2,3)$.

Figure 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).

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 (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.

$m, n_B + m$), 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 (12)) and $(n_C - 1, n_B - 1)$. The area of multiplicity with $(n_C + 1, n_B + 1)$ is given by

$$\begin{aligned} \pi_C(n_C+1, n_B) < \omega_C \leq \pi_C(n_C+1, n_B+1) \\ \pi_B(n_C, n_B+1) < \omega_B \leq \pi_B(n_C+1, n_B+1) \end{aligned} \tag{12}$$

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, 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 (11) and (ii) ω does not satisfy conditions (12). Assuming that ω follows certain distribution, it is possible to derive the likelihood function.

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

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

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 3 applies. Finally, per capita revenues depend on unobserved market-specific revenue shocks, ξ_i. Then,

$$\ln r_i(N_i,N_j) = X\lambda_i + \alpha_i^{N_i} + \frac{\delta_i^{N_j}}{N_i} + \xi_i. \tag{13}$$

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

$$\ln \frac{\mu_i(N_i,N_j)}{f_i} = X\varphi_i + \tau_i^{N_i} + \rho_i^{N_j} - \eta_i \tag{14}$$

Substituting (13) and (14) in (11), the entry conditions can be expressed as

$$X\beta_i + \ln S + \theta_i^{N_i+1} + \gamma_i^{N_j} < \omega_i < X\beta_i + \ln S + \theta_i^{N_i} + \gamma_i^{N_j}, \tag{15}$$

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

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

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

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

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

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

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.

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 $\Sigma_{\omega.\xi}$.

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 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 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 show a positive but decreasing pattern.

Most importantly, concerning the strategic interaction between different types of amenities, Table 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

Table 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.

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 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

[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.

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

$$\hat{S}(N_i) = \exp(-\bar{X}\hat{\beta} - \hat{\theta}^{N_i} - \hat{\gamma}^{N_j}). \tag{16}$$

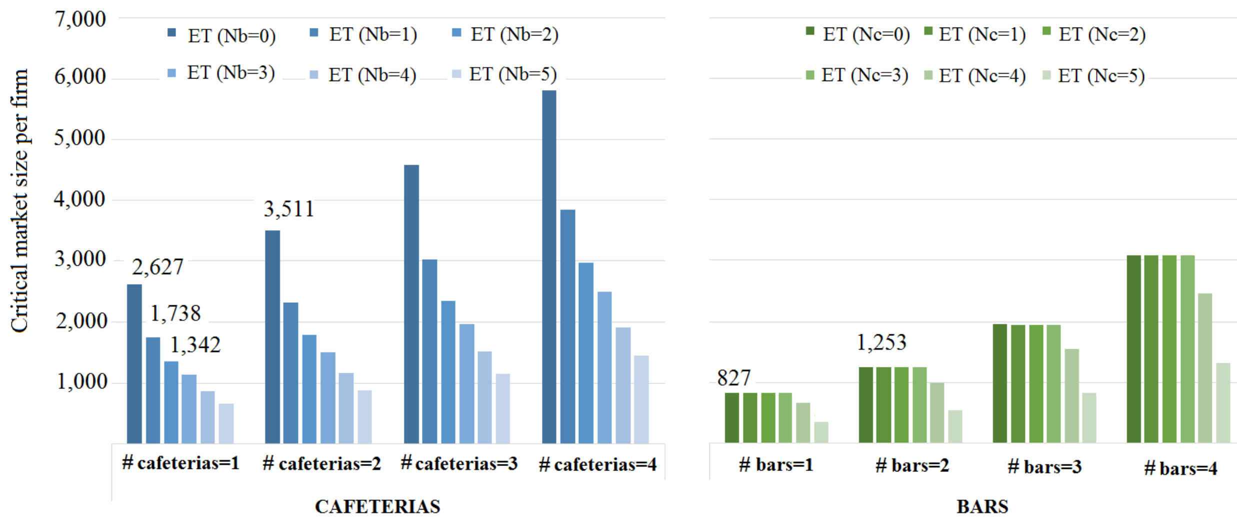
Changes in entry thresholds per firm $\hat{S}(N_i)/N_i$ are typically used as a measure of competition. A disproportional increase in population to support an additional entrant indicates that entry intensifies competition. Figure 3 illustrates how entry thresholds per firm vary under different market configurations.[17]

Following the structure presented in section 3.2, first consider cafeterias' entry thresholds (left

[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.

[17] All estimated entry thresholds per firm can be found in Appendix D (Table 8).

Figure 3: Spillover effects



Note: Estimated entry thresholds (see Equation 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).

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 3 clearly shows how positive spillover effects play a role for cafeterias (from bars' 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.

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.

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 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

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

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 (1991)). Given this, a change in per capita revenues from r to Δr enters the profit equation in the following manner:

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

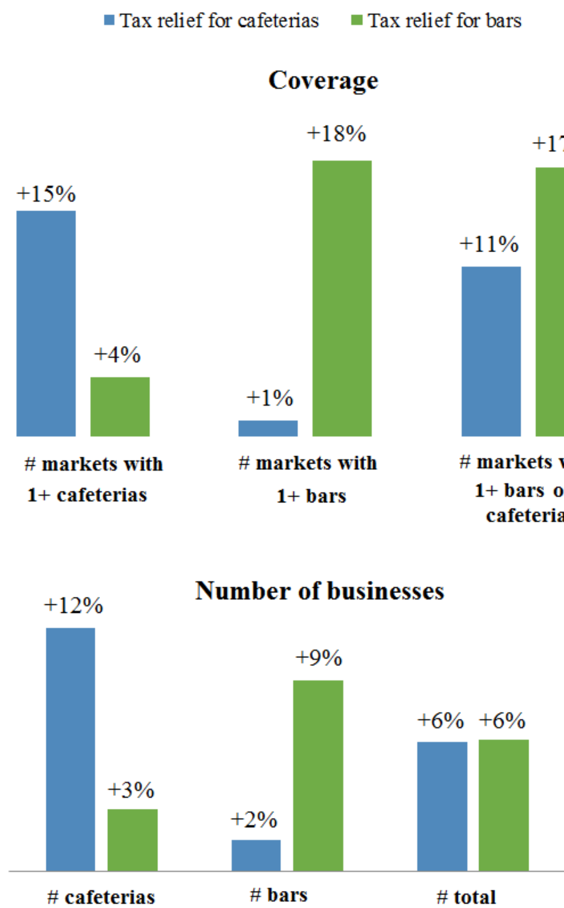
Firms enter if and only if $\Pi_i^*(N_i, N_j) > 0$. Equivalently,

$$\ln \frac{\mu_i(N_i, N_j)}{f_i} + \ln r_i(N_i, N_j) + \ln(\Delta) + \ln S - \omega_i > 0 \qquad (17)$$

I make new entry predictions by replacing (13) and (14) into (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 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% 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.

Figure 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.

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 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]

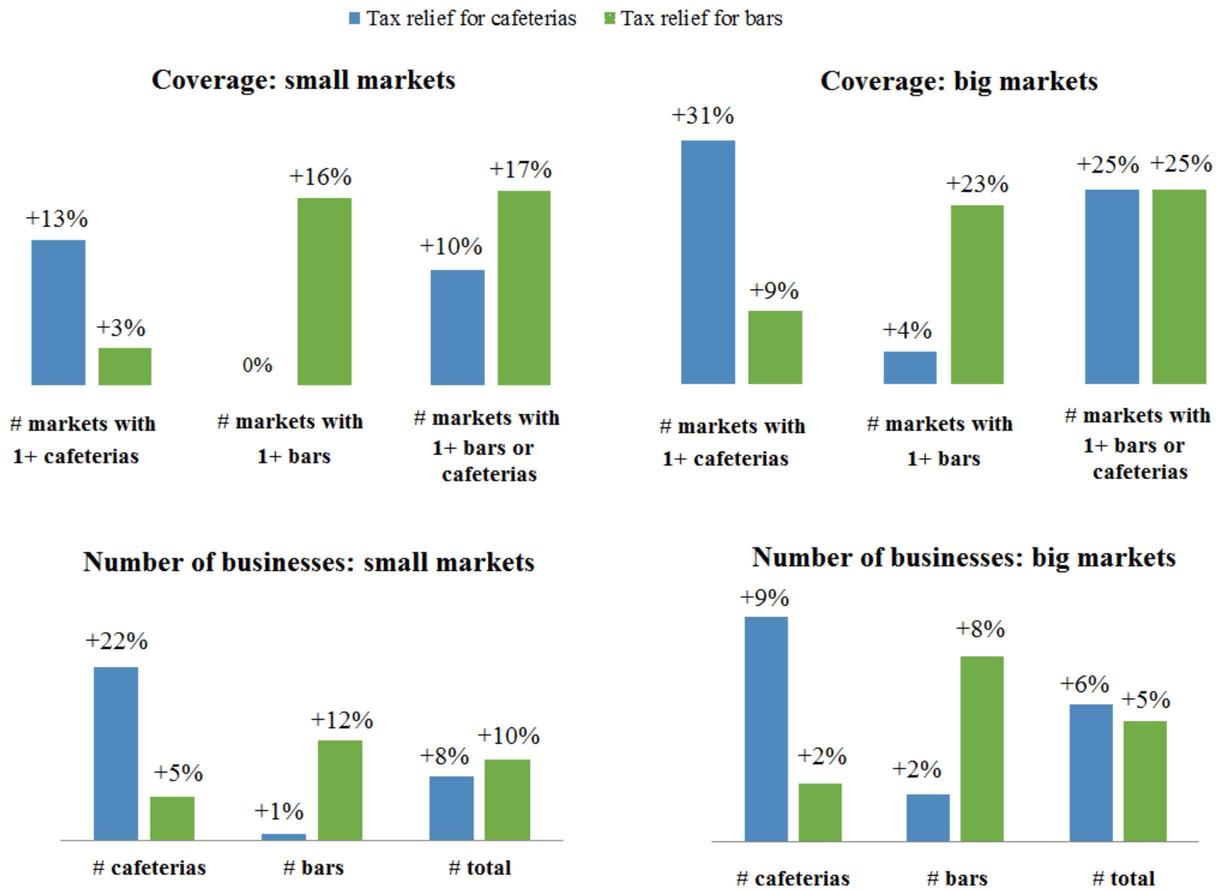
As the left part of Figure 5 shows, the spillovers of bars' entry over cafeterias predominate in small markets. Policies targeted to bars increases cafeterias coverage (+3%), as well as the number of businesses (+5%). These effects are larger than the one from cafeterias' on bars: geographic coverage 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 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.

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

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

Figure 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.

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 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 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

[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 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).

(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 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 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.

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.

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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 $f(.)$, 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

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

   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 $f_{\omega_C,\omega_B}(.,.)$ 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 $(N_C > 0, N_B > 0)$:

   - $\begin{array}{l} \ln r_C = X\lambda_C + \alpha^{N_C}_C + \frac{\delta^{N_B}_C}{N_C} + \xi_C \\ \ln r_B = X\lambda_B + \alpha^{N_B}_B + \frac{\delta^{N_C}_B}{N_B} + \xi_B \end{array}$

   - $\begin{array}{l} X\beta_C + \ln S + \theta^{N_C+1}_C + \gamma^{N_B}_C < \omega_C < X\beta_C + \ln S + \theta^{N_C}_C + \gamma^{N_B}_C \\ X\beta_B + \ln S + \theta^{N_B+1}_B + \gamma^{N_C}_B < \omega_B < X\beta_B + \ln S + \theta^{N_B}_B + \gamma^{N_C}_B \end{array}$

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

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

$f(\omega_C|(\xi_C, \xi_B), \omega_B|(\xi_C, \xi_B))$ 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

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

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

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

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

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

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
  $\ln r_B = X\lambda_B + \alpha_B^{N_B} + \xi_B$
- $X\beta_C + \ln S + \theta_C^1 + \gamma_C^{N_B} \quad < \omega_C$
  $X\beta_B + \ln S + \theta_B^{N_B+1} \quad < \omega_B < X\beta_B + \ln S + \theta_B^{N_B}$

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 5). Standard errors in parenthesis. *, **, or *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Appendix D. Entry thresholds per firm

Table 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 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 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 ($\Delta_B = 1.25$).