Micro-level adaptation, macro-level selection, and the dynamics of market partitioning

César García-Díaz
Department of Industrial Engineering, Universidad de los Andes (Colombia)
ce.garcia392@uniandes.edu.co

Arjen van Witteloostuijn
Tilburg School of Economics and Management, Tilburg University (the Netherlands)
Antwerp Centre of Evolutionary Demography (ACED), University of Antwerp (Belgium)
a.vanwitteloostuijn@uvt.nl

Gábor Péli
Utrecht School of Economics, Utrecht University (the Netherlands)
g.peli@uu.nl

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Abstract

This paper provides a micro-foundation for dual market structure formation through partitioning processes in marketplaces by developing a computational model of interacting economic agents. We propose an agent-based modeling approach, where firms are adaptive and profit-seeking agents entering into and exiting from the market according to their (lack of) profitability. Our firms are characterized by large and small sunk costs, respectively. They locate their offerings along a unimodal demand distribution over a one-dimensional product variety, with the distribution peak constituting the center and the tails standing for the peripheries. We compare our findings to the predictions of earlier dual-market explanations that focus on the macro (industry/population) level, pointing to commonalities, but also revealing a number of aspects for which our model extends knowledge on the pre-conditions and mechanisms of dual market formation. One novel result is the emergence of an endogenous minimum scale of production for low sunk cost firms that contributes to the stability of the dual structure. The withdrawal of large firms from the market periphery (enabling the small enterprises to scavenge on residual demand) is a well-known mechanism of dual structure formation. We found bi-directional center-periphery moves under a broad range of parameterizations: large firms may first advance toward the most abundant demand spot, the market center, and release peripheral positions as predicted by extant dual market explanations. Afterwards, large firms may then move back toward the market fringes to reduce competitive niche overlap in the center, triggering nonlinear resource occupation behavior.

Keywords: dual market structure, sunk cost, agent-based simulation, organizational niche, micro-level adaptation, micro-level economic behavior

1. Introduction

Many industries feature dual market structures, with a few large companies dominated the market's center and many smaller enterprises surviving in the market's periphery. Such dual market structures are associated with high concentration and high density. In industrial organization and organization theory, the question as to how dual market structures of two dominant firm types evolve has been studied since a long time [1, 2, 3]. However, to date, alternative explanations circulate in the literature that have not yet been integrated [4], implying that the evolution of dual market structures still not fully understood [5]. In this paper, we develop an agent-based simulation model to explore different dual market structure explanations, revealing how they can or cannot be integrated, and what additional mechanisms may well play a role.

Hitherto, little has been done in order to fully incorporate dynamic firm behavior in the selection-adaptation interplay in the context of population-level market positioning processes. A comprehensive understanding of the emergence and evolution of specific market structures should include insights from different perspectives. Key is that a microeconomic approach can provide the building blocks for a theory that offers a micro-foundation for macro-level market structuration processes [5, 6]. We argue that the development of such a micro-foundation in the form of explicitly modeling firm-level rules of behavior and interaction may indeed be an important contribution by integrating different arguments in the context of the study of market structures. We seek to integrate firm-level decision-making rules [7] in the context of horizontal product differentiation [8] into an industry-level approach through an agent-based computational model.

Our agent-based simulation model connects micro- and macro-level aspects of dual market formation. It runs in a one-dimensional commodity space [9] with a unimodal (peaked) demand distribution. Firms address audience tastes concerning product variants represented as ordered positions along the axis. We consider entry, competition, and (potential) coexistence of two types of agents: *L*-firms with large sunk costs and *S*-firms with low sunk costs. These agents can also differ in size and in their breadth of offerings for their respective audience (niche width).

This choice of settings relates our model to two extant dual market theories, one from Economics and one from Sociology. The unimodal demand distribution, with the demand peak representing a market center surrounded by peripheries, connects our approach to the (original version) of resource partitioning theory of sociological Organizational Ecology (OE) proposed by [2]. This model version is based on demand release at the market fringes inviting small firm entry to highly concentrated markets.[1] Letting firms with low/high sunk cost operate in this demand landscape establishes a link to the economic dual structure explanation of [1] in Industrial Organization (IO). By choosing this configuration, we also aim at getting new insights on the commonalities between these theories' underlying disciplinary domains – IO and OE, respectively – known to exist but unexplored for about two decades [6].

From an IO perspective, [1] explains how game-theoretic equilibria might lead firms to incur short-run (so-called endogenous) sunk costs. This is the result of firms' profit-maximizing decisions whether or not to invest in advertising or innovation. The sunk costs can be recouped by focusing on brand recognition and increased consumers' willingness to pay through product differentiation. The equilibrium

[1] Another stream of resource partitioning arguments explains small firms' making foothold at the market fringes with their oppositional identities they establish against large center incumbents [3, 10]. These identities oftentimes include anti-mass production sentiments, like in case of the American microbrewery movement [11]. Please note that from now on, when speaking about resource partitioning, we solely focus on the mechanism based on demand release because of its inherent link to standard economics' thinking.

outcome may be a dual market structure in which two types of firms (or strategies) co-exist. On the one hand, in order to recover the sunk cost investments, high investment firms target high demand areas with the intention of reaping scope economies [4]. Thus, large multi-product generalists take over the market's central region by offering an investment-intensive portfolio of products. But firms that cannot afford such huge investments in advertising or R&D play a different game, opting for a radically different strategy. Since product differentiation and brand recognition are not attainable for low-investment firms, these firms at the market's fringes focus on becoming single-product specialists that operate low-cost strategies. The co-existence of large high-differentiation multi-product generalists along with small low-cost single-product specialists is the essential feature of Sutton's dual market structure.

Alternatively, resource-partitioning theory (OE) explains the emergence of dual structure with narrow-niche (specialist) organizations and broad-niche (generalist) organizations in times of increasing market concentration [2].
The argument is based on three critical assumptions: (i) consumer demand is distributed along a unimodal distribution with a market center; (ii) taste heterogeneity among consumers is sufficiently large; and (iii) the industry exhibits strong scale economies in the center of the market, and strong scope economies across the market center and periphery. Large-scale firms (oftentimes 'generalists' targeting a broad range of consumer tastes) will mostly make use of scale economies and compete for the market center abundant in demand. Increased competition in the center leads to consolidation, forcing out many large players and so freeing up positions on the periphery. The bottom line is that the consolidation of generalists in the center, which increases market concentration, creates the conditions for specialist proliferation at the market fringes [12, 13].

Our simulation model is not, and does not aim to be, a specific computational implementation of these two theories. But in the course of the simulation process, we found remarkably strong correlations evolving with time between their key concepts along a substantially broad range of parameterizations. In general, large sunk cost firms can be small at certain phases of their life cycles, and low sunk cost firms may occasionally grow relatively large. Similarly, some small generalists may survive in lack of competition, while some specialists may grow reasonably large if they find uncontested islands of demand [14]. But our simulations revealed a strong tendency that being large in scale, in scope (niche width) *and* in sunk cost coincide to a large extent (Figure 1), provided that the microeconomic conditions of firms' entry, exit, offering and competitive engagement assumed in our model apply. Similarly, with the same conditions in place, being small, being specialist and having low sunk cost strongly correlate, too.

This endogenously evolving convergence between our model concepts, as visualized in Figure 1, offers possibilities for exploring linkages between different dual market explanations. We evaluate these commonalities in the concluding part. There, we also discuss explanations for those simulation findings that go beyond extant market partitioning predictions, so broadening the known repertoire of cases/causes of dual market formation. As is the case with all simulation studies [15], the findings are only justified for the given model settings. But within our setting, the reported results are robust: they have been observed under a broad range of parameterizations.

[INSERT FIGURE 1 ABOUT HERE]

2. The model[2]

Close to the spirit of evolutionary games, we study the evolution of performance of two market strategies differentiated by initial sunk cost investment.[3] Firms compete in a market characterized by scale economies and niche-width (scope) diseconomies. We take the work of [4] as our steppingstone, who argue that the large / small sunk cost firm types reproduce dual market structures in multi-product settings, similar to the generalist / specialist context in resource partitioning. So, linking to the IO literature [1], we consider large versus small sunk cost types: large sunk cost firms can and small sunk cost firms cannot benefit from scale economies. Specifically, firms with

[2] To prevent being overloaded with technicalities, the main text describes the essence of the model and highlights how the corresponding formal constructs work. The detailed formal account of the model's equations, parameter descriptions and their value ranges applied at sensitivity analyses is available in the Materials and Methods section.

[3] An additional reason to keep only two market strategies comes from knowing that significant firm entry diversity, represented by very few and contrasting firm types, is needed to generate dual market structures with few dominant firms at the market center and a considerable number of small players at the periphery (cf. [16]).

large sunk costs (*L* firms) invest in large production capacity and aim to be efficient in the long run. Firms with small sunk costs (*S* firms) are cost-efficient at the time of market entry, but their sunk cost investment is insufficient to be cost-efficient in the long run. Due to the niche-width related negative effects, as we will explain below, *S* firms take advantage of a strategic location at the market fringe, where scale-based competitors have no efficient reach because the scope diseconomies of niche spanning cannot be compensated by scale economies.

Firms offer a single price for their whole niche. Scale advantages are translated into lower prices, and consumers buy from the cheapest producer in their niche. Firms use a markup price in order to reflect their scale advantages, provided that such a price does not exceed the consumer's participation constraint. Consumers also take into account the negative effect of product dissimilarity, which is the distance between the firm's niche center and the consumer's location. Firms seek to increase their scale advantage by expanding their niches, but large-niche firms need to offer low enough prices in order to keep consumers at the niche edges satisfied.

Attribute space and location specification at entry

Our attribute space is a commodity space [9] with one product dimension along which each firm offers a single product or service. Customers' taste preferences are represented by their ideal points along this single dimension.[4] We can think of every time period in the simulation as roughly representing a period of one month. The simulation model always starts with one single firm, and firms enter the market at a constant rate x per time period if the space is not completely occupied. The entry rate varies from 2 to 3. This range setting fits, for example, the American automobile industry, which has exhibited dual market characteristics over its history [3], registering approximately three thousand active firms over its first hundred years of existence [18]. The attribute space corresponds to a unimodal distribution of consumers b_k, $k = 1, 2, \dots, N$, where N represents the total number of taste positions.

[4] Some attribute space models consider organizations' clientele distributed across variables in an N-dimensional *Blau-space* of socio-demographic characteristics [17]. Our space representation is not sensitive to the choice as to whether the demand curve is drawn over socio-demographic characteristics or taste positions.

The attribute space is furnished with demand according to a beta distribution with parameters $\alpha = \beta = \eta > 0$. This assures a unimodal distribution with a finite number of taste positions. For the baseline model, we take $\eta = 3$ and $N = 100$. All simulation runs are performed using total demand of $\sum_k b_k = 5{,}500$ consumers. Firms that enter the market set their niche location according to the probability distribution of non-served consumers: higher crowding at a taste location tends to repel entrants.

Firm's cost structure

Building/securing market positions involves costs that increase with the breadth of the niche the firm establishes or sustains. Accordingly, our single-product firms have two-piece cost functions. One piece relates to the production costs $C^i_{PROD,t}$, while the other accounts for niche-width costs, $C^i_{NW,t}$:

$$C_t^i = C_{PROD,t}^i + C_{NW,t}^i . \tag{1}$$

Production level of firm i at time t (Q_{it}) is quantified through a Cobb-Douglas function [19]:

$$Q_{i,t} = F_i^{\alpha} V_{i,t}{}^{\beta} . \tag{2}$$

F and V denote production factor quantities that contribute to fixed (sunk) and variable costs, respectively. Firms derive their production costs ($C^i_{PROD,t}$) from the long-run average cost curve ($LRAC$) of the whole industry. The $LRAC$ curve is the envelope of the most efficient production possibilities in the industry. We assume that $\alpha + \beta > 1$ in order to have a downward-sloping $LRAC$ and so positive scale economies. Production costs for the firm are calculated according to the usage of production factors F and V that the firm needs to produce quantity Q. That is, assuming that production factor prices are W_F and W_V, respectively, the $LRAC$ curve is calculated by solving the following optimization problem:

$$\begin{aligned} \min \quad & W_F F_i + W_V V_i \\ s.t. \quad & Q_{i,t} = F_i^{\alpha} V_{i,t}{}^{\beta} \end{aligned} . \tag{3}$$

The production cost of every firm i, $C^i_{PROD,t}$, is computed assuming that the firm has a fixed usage of factor F, independent from production levels (that is, $W_F F_i$ represents firm's fixed costs). Entrants are linked to either of two levels for F, large or small, with equal probability. These levels define the two firm types in the model: L firms and S firms are characterized by high and low levels of fixed cost-related production factors, respectively. Niche-width costs represent the negative effect of producing for a broad range of consumer preferences. For instance, attempting to serve a greater variety of consumer preferences might induce the firm to incur in additional advertising and merchandising costs. The cost of serving a consumer taste portfolio increases with taste heterogeneity. Firms' niche-width costs are proportional to their niche span:

$$C^i_{NW,t} = NWC\left\| w^u_{i,t} - w^l_{i,t} \right\|, \tag{4}$$

where NWC is constant, $\|.\|$ denotes Euclidean distance, and $w^l_{i,t}$ and $w^u_{i,t}$ represent the firm's lower and upper niche limits, respectively. A firm's niche center stands halfway between the lower and upper niche limits.

Consumer behavior

Each consumer buys once every time period. $S_{k,t}$ denotes the set of firms that have an offer at position k. Just like in Hotelling-type address models [8, 9], consumers' displease increases with the distance between their ideal taste point and the offering. The 'product dissimilarity cost' the consumer perceives is measured as the distance between her ideal point and the offering firm's niche center. Accordingly, consumers buy from the firm that offers the lowest $U^*_{k,t}$ compound cost (price plus product dissimilarity):

$$U^*_{k,t} = \min_{i \in S_{k,t}} \left\{ P^i_t + \gamma \frac{\left\| nc^i_t - k \right\|}{(N-1)} \right\}, \tag{5}$$

where P^i_t is firm i's price at time t. Note that product dissimilarity is normalized by the maximum possible Euclidean distance in the product space, $N-1$.

If the selected firm cannot fully satisfy demand, the consumer buys from the second cheapest alternative, and so on. Since the $LRAC$ curve reflects the efficient production frontier (in terms of costs) as a function of quantity, and the curve is downward-sloping as Q increases, the highest cost value is the one that corresponds to the smallest quantity. We assume that this maximum cost value – the smallest efficient production quantity – is a reference point of the maximum price a consumer is willing to pay: $P_{max} = (1+\varphi)LRAC\,|_{Q=1}$. Coefficient φ stands for mark-up pricing (Adner &

Levinthal, 2001). The value of φ is set between 0 and 1. We use $\varphi = 0.2$ for our baseline model. If a consumer buys from firm i^*, the price $P^{i^*}{}_t$ paid cannot exceed this maximum price compensated by the negative effect of product distance from the customer's ideal taste point:

$$P_t^{i*} \le P_{\max} - \gamma \frac{\left\| nc_t^i - k \right\|}{(N-1)}. \tag{6}$$

In order to reflect scale advantages, firms use a mark-up price over average costs, given as $(1+\varphi)C(Q)/Q$. Therefore, a firm will set a price $P^{i^*}{}_t$ that is the lowest of (a) its markup price and (b) the maximum bearable price the most distant consumer within its niche would pay (Equation (7)):

$$P_t^{i*} = \min\left[P_{\max} - \gamma \frac{\left\| nc_t^i - k \right\|}{(N-1)}, (1+\phi)C(Q)/Q \right] \tag{7}$$

Entry price setup

Firms enter at one single position in space, searching for a competitor-free foothold to enter the market. Thus, firms look for residual demand (non-served consumers) at the different points in space. Entry probability at a location increases with the size of residual demand. For each potential entry position k, the firm calculates potential production quantity $Q = (1 - CBP_k)b_k$, based on the amount of residual demand at k. Subsequently, the firm sets the unit price as described in Equation (7) above. A characteristic of the S firms is that they are able to make profits at the time they enter the market. But L firms may need some time to reach an operation scale that allows them to generate positive profit. Thus, we assume that L firms have an initial endowment that helps them going through this growth period [20]. Endowment E is reflected in the number of time units during which a firm can survive without sales. For the baseline model, we set $E = 12$.

Firm expansion

Firms can expand horizontally (in breadth) and vertically (in depth). Horizontal expansion takes place through widening the niche, while vertical expansion means increasing sales within the given niche. In line with behavioral theories of bounded rationality [21, 22], we assume a simple search heuristic when computing the maximizing option would be complex. Our firms are prudent observers that base their actions on their rivals' past behavior [23]. The expansion being either horizontal or vertical, the firm first decides upon a target quantity based on the latest observed prices and costs. Subsequently, the firm computes expected incremental profits and decides if expansion is worth the investment.

As said, vertical expansion is a production quantity adjustment at fixed niche breadth. At time t, firm i makes production adjustments for the next round t+1 and targets the residual demand $\Delta Q_{v,t+1}$ in its current niche. Then, the firm evaluates whether incremental revenues surpass incremental costs.[5] If so, the firm decides to expand. Horizontal expansion takes place by increasing niche width. The firm estimates target quantities $\Delta Q^{u}_{h,t+1}$ and $\Delta Q^{l}_{h,t+1}$ at both side of its current niche, and decides to expand in the more attractive direction – if there is any. Niche expansion is controlled by expansion probability, *ExpCoef*.[6]

The quantities $\Delta Q^{u}_{h,t+1}$ and $\Delta Q^{l}_{h,t+1}$ are set as follows. Assume that there are two firms, *A* and *B*, serving the same taste position. The position has a total demand of ten consumers, and the compound costs consumers perceive at that position are $U(A) = 10$ and $U(B) = 15$ with captured demands $Q(A) = 7$ and $Q(B) = 3$. If firm *C* attempts to enter that position, and assuming that $U(C) = 12$, the ascendant cost ranking will place firms in the following order: *A*, *C*, and *B*. Firm *C* estimates that *A* will keep its previous period's demand in the next round (i.e., $Q(A) = 7$), since *A* still has the cheapest offer. But now, given that *C* has a better offer than *B*, *C* will steal B's demand and estimate that in the next round $Q'(C) = 3$ and $Q'(B) = 0$. In a similar fashion throughout the simulation, firms estimate their next round's demand for the case of horizontal expansion, and quantify its benefits by calculating potential incremental profits. Since the potential expansion re-locates the niche center as well, the new price reflects the new distance compensation to the customers at other locations. The firm then performs the same incremental profit calculation concerning the lower niche limit, and opts for the more lucrative expansion direction (if any).

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[5] Another possibility is that firms also target absorbed demand (i.e., demand already served by other firms). However, this would involve modeling strategic pricing behavior, which would dramatically complicate our model.

[6] Since we first run the model for 2,000 time periods, our criteria is that an *L* firm has enough time to fully expand up to its fundamental niche, even if it enters the market at a mature state (> 1,000 time periods). Values for the expansion coefficient were chosen between 0.03 and 0.05.

3. Experimental design

We perform a hazard rate and a regression analysis of parameter variations on our key model variables, and industry concentration and firm density. We estimate a piecewise constant exponential hazard rate model. Firms may have a strongly age-sensitive baseline hazard function when the firm is very young, followed by longer spells with a more stable hazard as the firm grows older. Therefore, we define a fine-grained youth period characterized by short time intervals, along with longer intervals for older ages: [0,10), [10,20), [20,30), [30,40), [40,50), [50,60), [60,70), [70,80), [80,90), [90,100), [100,200) and [200,∞).

Our independent variables are niche width (*NW*), firm size (*Size*, measured as sold volume), distance to market center (*DC*), market concentration (*Gini*)[7] and firm type (*Type* = 0 for *L* firms, and *Type* = 1 for *S* firms). As control variables, we include industry age (*Indage*), active market size (*Mass*, measured as total sold volume), and firm density (the active population of firms in the market). After inspection of the correlation matrix, we decided to remove niche width from the list of variables as this revealed a high positive correlation with firm size. So, as indicated above, in our model, broad niche firms (generalists) are large, and small firms have narrow niche (specialists). We also found a high positive correlation between firm density and market concentration. Consequently, firm density has been eliminated from the list of control variables, too.

First, we study the hazard rate effects in different representative scenarios defined according to variations in small sunk cost investment (Q_S), product dissimilarity (γ), endowment (E), entry rate (X), markup value (φ), and expansion probability (*ExpCoef*). These scenarios correspond to models with mid-range parameters (Scenario 1), and to models with variations in small sunk cost investment (Scenarios 2, 3 and 4), markup (Scenarios 5 and 6), product dissimilarity (Scenarios 7 and 8), endowment (Scenarios 9 and 10), probability of expansion (Scenarios 11 and 12) and

[7] To increase robustness, we have experimented with both the C_4 ratio and the Gini coefficient as concentration measures. Oftentimes, we found very high correlation between the two; see the visual results in Section 5. However, since the Gini coefficient reveals a clear monotonic behavior, we preferred to use this as a proxy for market concentration in the statistical analyses.

entry rate (Scenario 13). Detailed parameter specifications for all scenarios are provided in the Materials and Methods section. Additionally, we examine the behavior of our main time-evolving variables of interest – i.e., market concentration, per-type density, and per-type total covered market space. Each of the 13 scenarios was run 30 times for 2,000 time periods. Each run produced more than 100,000 duration-related observations.

We measure the occupied space per firm type as the aggregated number of niche positions in which this firm type realizes sales. When *L* firms focus on the positions with the most consumers, they abandon unattractive taste positions with scarce demand that do not counterbalance their increased scope costs. Accordingly, we measure the space released for *S* firms by the contraction of total space occupied by *L* firms.

The second analysis considers market concentration, *L* firm density, *S* firm density, and *L* firm space contraction as dependent variables. The independent variables are small sunk cost (Q_S), product dissimilarity (γ), markup (φ), endowment (E), expansion probability (*ExpCoef*), and entry rate (X). The description of the 4 x 3^4 x 2 = 648 parameter value combinations applied is included in the Materials and Methods section. We follow standard simulation procedures to explore model behavior under different parameterizations (for details, see [24]), and estimate an OLS regression model with the variables mentioned above. The OLS estimators were computed as

$$\hat{\beta}_i = (X'X)^{-1} X\overline{y_i}\,, \tag{8}$$

where $\overline{y_i}$ is the i^{th} simulation output (i = 1,…,4), and X is the parameter value matrix. Every parameter combination is averaged out over five runs, giving 3,240 observations in total. To better capture steady-state parameter variation effects, we have run each simulation for 5,000 time periods, averaging the key outcome variables for the last 500 time units.

4. Results

Concentration and market structure

As said, market concentration was measured with the compound share of the four largest firms (C_4) and with the Gini coefficient. C_4 first declines as the market gets populated with firms (recall that the model starts with only one firm), then it turns increasing as dominant *L* firms gain market share and grow large (Figure 2a). While *L* firm density declines, *S* firm density first rapidly increases and then slowly moves towards a high value. The Gini coefficient starts increasing from a low value and stabilizes at around 2,000 time periods (Figure 2b). These evolution patterns prove to be fairly consistent across all scenarios. Figure 2c displays a representative sample of density change patterns. The thick line represents average (mean) behavior. The shadowed regions are confidence intervals at 95% over the mean. All results reported below apply to markets with a unimodal demand distribution and type heterogeneity with *L* and *S* firms.

[INSERT FIGURE 2 ABOUT HERE]

L firms' number reaches a peak before scale-based competition triggers a decrease. The number of *S* firms follows an S-shape, first soaring with *L* firm shake-out and then settling in the long run (even turning mildly declining under some scenarios; see Figure 2c). In the long run, the numbers stabilize for both types, indicating the existence of dual carrying capacity in the market. That is, the market dual carrying capacity provides resources for two stable niches – a center and a periphery. Still, *S* firm density stays systematically higher over the whole simulation period.

Figure 3 displays the space-related selection effects of scale-based competition. We plot the size distribution of firms *vis-à-vis* their distance from the market center across different scenarios. Large-sized, broad-niche *L* firms reside in the market center, completely kicking out *S* firms from the center, while narrow-niche players (with a dominant population of *S* firms) proliferate at the market fringes.

[INSERT FIGURE 3 ABOUT HERE]

Outcome 1. *(a) As the market gets crowded, market concentration increases; (b) large sunk cost (L) firm density first increases and then declines, while small sunk cost firm (S) density increases; and (c) Broad-niche firms (typically of the L type) take* *over the center, whilst narrow-niche firms (a mixture of L and S firms) locate at the market fringes, producing a dual market structure, with narrow-niche firms' density systematically being higher.*

[INSERT FIGURE 4 ABOUT HERE]

Scale-based competition and space release

Next, we analyze the change pattern of *L* firm space coverage over time. We investigate whether *L* firms move toward the center and whether their involvement in scale-competition indeed generates space release at the market's peripheries. We found that while *L* firm density declines after reaching a peak, the total space occupied by *L* firms first arrives at a maximum, then declines, and finally increases again. The few *L* firm survivors normally keep growing and continue to conquer additional niche positions. As a result, the total *L* firm space oftentimes reveals a non-linear behavior, as can be seen in Figure 4.

Outcome 2. *Scale-based competition in the market center may cause space release at the market semi-periphery. But in the long run, large firms re-occupy (some of) the abandoned space.*

Strong firm shake-out at central market positions pulls the surviving large firms toward the center, so igniting demand release at the market fringes. Our results also indicate that a portion of the *L* firms return to the (semi)peripheries. There is an intuitive explanation for this 'pendulum' effect. The downfall of large firms frees up a substantial slice of once-served demand, pulling the surviving *L* firms toward the center. Since survivors act similarly, this may lead to a kind of overshoot effect: center competition will increase, again, dramatically, making niche extensions toward the peripheries profitable. Also, surviving firms may have not yet reached their minimum efficient scale point at the moment of departure of dying firms: i.e., survivors may still be able to decrease unit production costs by expanding. Such a reduction in unit costs may still dominate over scope diseconomies, allowing survivors to capture more demand than had been released before by departing firms. This dynamics contributes to a loss, and then to a subsequent recovery, of demand by market-center players.

Hazard rate analysis

We performed a hazard rate analysis for each individual simulation. Then, each coefficient was averaged over all simulation runs. Average coefficient values, the standard deviations and the percentages of time for which the variables have been found significant are provided in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Our results confirm that firm size decreases the risk of mortality [25, 26]. Moreover, market concentration, measured with the Gini index, increases mortality for all firms, large and small alike. *S* firms have a higher risk of mortality than *L* firms over the whole simulation time. Moreover, we observe that a firm's distance to the market center monotonically increases its mortality risk.

Outcome 3. *Mortality risk decreases with firm size, whilst increases with market concentration and with the distance to the market center.*

The simulation results demonstrate that very few *L* firms succeed in taking over the center. The majority, mostly narrow-niche (and small-sized) *L* firms, normally stay at the market fringe, but live short and die eventually. However, the few long-standing *L* firm survivors become the strongest and largest firms in the market. The strongest *S* firms are those that have benefited from scale economies (reaching a relatively large size of 50-100 units). However, they remain located in the market periphery. To investigate the differential impact of firm size on firm type as market concentration increases, we estimated models with three-way interaction terms of *Type* × *Gini* × *Size*. The minimum and maximum coefficient values are presented in Table 4. We found all coefficients to be negative and significant at $\alpha = 0.05$. This implies that *S* firms' mortality hazard would, ceteris paribus, increase with concentration, but this extra hazard is offset by their size gain effect.

Additionally, we computed the hazard rate multipliers per scenario (see [27, 28]. Here, hazard rate multipliers account for the effect of market concentration on the mortality rate per firm type across different firm sizes, as illustrated in Figure 6. We found across all scenarios that large-sized *S* firms had lower mortality risks than small-sized ones as market concentration goes up. This effect was size specific: whereas the smallest *S* firms experienced higher mortality hazards with rising concentration, the largest ones faced a decrease. For *L* firms, the impact of firm size on mortality varied over scenarios. But the *L* firm multiplier did not decline with firm size under any scenario (Figure 5). These findings allow for two possibilities for the case of increasing market concentration: either the mortality hazard increases slower for the largest *S* firms than for *L* firms (Figure 6a), or the mortality hazard decreases for the largest *S* firms whilst increases for all *L* firms irrespective of their size (Figure 6b).

[INSERT FIGURE 5 ABOUT HERE]
[INSERT FIGURE 6 ABOUT HERE]

Outcome 4. *As market concentration increases, either* (i) *large S firms' mortality hazard decreases whilst that of L firms' does increase or* (ii) *S firms' mortality hazard increases at a slower pace than that of L firms; (iii) the smallest S firms' mortality hazard always increases with concentration.*

So dual market structure may also develop when increasing concentration raises *S* firms' hazard less than that of *L* firms. This outcome also indicates having an endogenous *minimal scale of production* as an emergent property in our simulation model: the very small players disappear. Small niche players falling below this minimum scale cannot benefit from the space release induced by increasing concentration. This indicates that the dual structure is developed by having large and small (but not extremely small) firms.

Outcome 4 reveals that size effects operate differently on *L* and *S* firms. For *L* firms, increasing size weakens the intensity of the concentration-related mortality effect; however, the effect always stays increasing. For *S* firms, concentration might either increase or decrease mortality. The broad range of size-related simulation outcomes we have studied reveals that two types of partitioning, a weak and a strong one, can emerge:[8] as concentration rises, either *L* firms and *S* firms experience increasing and decreasing mortality (strong partitioning), respectively, or both experience increasing mortality, with *S* firms' chances deteriorating at a slower pace (weak partitioning).

Regression results

As explained above, our OLS regression analysis takes the simulation model's parameters as independent variables out of 3,240 observations. In 17 observations, the market has become extinct long before the end of the simulation's time horizon. Our four dependent variables were, again, average market concentration (*Gini*), *L* and *S* firm density average over the last 500 time periods, and space release. The last effect is proxied with *L* firm space contraction (*Lcontr*), the difference between maximum and average space occupied by *L* firms in the last 500 time periods.

[INSERT TABLE 2 ABOUT HERE]

Our estimates are presented in Table 2.[9] Market concentration was found to be negatively correlated with the small sunk cost parameter Q_S and product dissimilarity γ. This is in line with expectations, since increasing *S* firm scale advantages and distance-related effects both lower the scale advantage of *L* firms.

As expected, *L* firm space contraction (*Lcontr*) is larger when Q_s is larger, because increasing *S* firm scale decreases the competitive advantage of *L* firms. Our interpretation is that *L* firm space contraction is partially due to their direct competition with *S* firms. This also suggests that *L*-firm's space release in the peripheries is not necessarily triggered by increasing market concentration, as quite a few earlier studies observed in industries with a generalist-specialist dual structure [2, 13]. Here, our generic *L*-*S* firm model identifies broader conditions under which dual structure can occur. We found a positive correlation between *L* firms' endowment (*E*)

[8] This finding resembles to the strong and weak patterns of partitioning observed in the dual-market study of Boone et al (2000) on Dutch auditing firms.
[9] The minor non-normality of the residuals is not relevant as we have a large number of observations. In order to deal with heteroskedasticity, we ran our regression with robust standard errors whilst iteratively computing weighted least squares. The results were quite similar. Here, we only report the OLS estimates.

and the contraction of space occupied by them. Higher endowment provides larger endurance for *L* firms, offering protection against negative effects of market center crowding, thus allowing them to stand longer in the crowded market center. A higher capacity to endure competition at the center intensifies competitive overlap and triggers subsequent resource uncovering in peripheral market areas. A recent empirical study of Italian television broadcasting [29] illustrates that intensification of competitive overlap at the market center alone does support space release at the peripheries, even with concentration remaining invariant. In line with our simulation results, this empirical example supports the finding that large *L* firm endowment may even help small firms gain and maintain a foothold at the market fringes.

Moreover, we found that as the niche expansion coefficient (*ExpCoef*) increases, *L* firms grow faster, leading to lower *S* firm density. Additionally, our results indicate that *L* firms' larger expansion capabilities come together with their smaller space loss; their higher expansion probability is not only associated with their ability to move toward the market center, but also with their larger niche position takeover and, consequently, with having less space left for *S* firms to grow.

Outcome 5. *L firms' higher expansion probability and higher endowment allows them moving toward, and enduring competition in, the market. A higher L firm expansion probability decreases S firms' space release at the peripheries, while higher L firm endowment favors it.*

Outcome 5 suggests that enhancing the adaptive capacity of central market players to compete has two opposing effects, depending on whether the enhanced capacity comes from resilience (captured by endowment) or from flexibility (captured by expansion probability). Increasing competitive resilience may increase *L* firms' tolerance to near-center overlap, consequently lessening their interest in the market peripheries. Moreover, adaptation through higher expansion abilities allows *L* firms to move easier across the space, so exercising a negative effect on *S* firms' space covering. Our results indicate that assigning different levels of adaptive capabilities to firms through varying endowment and expansion abilities can extend the range of possible dual market outcomes. We hypothesize that adaptive capability level differences between firms can weaken or reinforce partitioning outcomes in a broad range of industries.

5. Discussion and conclusions

Our simulation results demonstrate that the set of large (typically generalist) firms to a large extent coincides with the set of large sunk cost firms when the microeconomic conditions adopted by our model are combined with a market center-periphery distinction. Several of our simulation settings yielded dual market outcomes that are similar to those predicted by other dual market approaches. This is, very likely, a consequence of the resemblance of our model assumptions to assumptions of these other theories. For example, our firms are characterized by a low/high sunk cost distinction (just as at [1]) interacting in a market with a unimodal demand landscape (just as at [2, 12, 29]). But the simulations also reveal aspects of dual market formation, which, according to our knowledge, have not yet been addressed by other theories. Below, we begin with the commonalities. This is followed by a summary and interpretation of those findings that provide new insights on the causes and ways of dual market formation.

Our results corroborating extant knowledge are as follows. Market concentration, measured with the Gini index, increases mortality for all firms, large and small alike (outcome 3). This is line with IO's argument as to the entry barrier and market power effect, as well as with main effect results from empirical market partitioning studies (like the one of [28] on the dual market structure of the Dutch auditing industry). We found space release at market peripheries with scale-based competition (outcome 2) and with subsequent large firm shake-out at the market center. This finding shows a clear analogy to documented cases of dual structure formation with center and peripheral market players [2] (outcome 1). Even with a modest space release in place, small *S* firms experience decreasing mortality rates with rising market concentration, while large *L* firms' mortality hazard increases in the meantime (outcome 4). Distance to the center is a determinant of the mortality hazard (outcome 3). Also in line with extant knowledge, we found that a noticeable level of firm heterogeneity – measured in terms of sunk cost magnitudes in our case – is necessary to generate a center-periphery market partitioning (cf. [16]).

The next findings reflect new insights that add to the extant literature on dual market formation in particular, and to theories of market dynamics in general. The first concerns the role of price mechanisms in market partitioning processes. From the very beginning [2], resource-partitioning theory has focused on markets where price was not the central aspect for customers (like in case of newspapers and microbreweries) or where price effects are suppressed by other aspects like reputation or the bundling of the offerings (such as in case of auditing services). We have demonstrated that a dual market structure with center-periphery partitioning can well occur when agents are sensitive to price.

Second, the effect of concentration on firm type (*L* and *S* firms) is moderated by a size effect. We found that that there is an emergent (endogenous) minimum scale of production that allows *S* firms to confront the negative effects of market concentration and their distance to the market center as well (outcome 4). Size effects can establish a concentration-dependent mortality threshold. Thus, the smallest *S* firms might though avoid head-on competition with market-center players, but still might succumb to other, somewhat larger, *S* firms.

Third, we found a temporally non-monotonic space release effect (outcome 2). *L* firms may first move out from the center in order to lessen competition, so occupying rather more than less (semi-)periphery positions. This happens because large sunk cost *L* firms might not yet operate close to their full scale potentials; their 'efficiency slack' can be used up to counterbalance scope diseconomies, and to expand, in the early consolidation phase. Occasionally, *L* firms may even take over more space than had been released. Later, when shake-out frees up additional affluent center demand that survivor *L* firms can efficiently capture, the relative advantages of aiming at scarcer periphery demand lessen, while *L* firms' scope diseconomies at the peripheries remain the same. At this mature phase, we found the space occupied by *L* firms contracting. The bottom line is that scale-based competition at the market center, alone, might not be enough to generate space release. Moreover, *L* firms may operate below their optimal scale at the time increasing concentration appears, so that space release might just partially emerge. Then, space gains, if occur, come at the expense of *L* firms failing because of the pressure of those *S* firms that managed to reach a certain size. Again, size effects per firm type operate in such a subtle way that while *L* firms do not get any benefit from increasing market concentration, some larger *S* firms do experience mortality hazard decline.

Fourth, enhanced adaptive capabilities of *L* firms (either through endowment or increased expansion chances) have effects on resource release (outcome 5). The magnitude of these capabilities (relative to each other) positively or negatively affects resource release. Previously, [5] had claimed that the nature and degree of (scale and) scope economies are key in understanding the precise equilibrium market structure outcomes. Here, we add that the interplay between market-level selection forces and firm-level adaptive capabilities we have introduced to our model gives room for the emergence of a large number of new dual market outcomes.

Finally, we found connections to some other domains of market dynamics research. The *L* / *S* firm distinction allows connecting our framework to research on the efficiency / efficacy duality [30] and the first-mover / efficient producer dilemma [31, 32]. Concerning the first, newcomers to the market may be efficacious (effective) but not efficient. They are efficacious in the sense of matching the environment – that is, in identifying some attractive positions with positive demand to which these firms can align their niche centers. Firms also gradually approach efficiency as they gain experience through competition [33, 34]. However, such environmental matching becomes more complex when a firm grows, and has to comply with multiple niches and the associated matching requirements – a complexity that can be counterbalanced with *L* firms' positive scale advantages. We observed that efficient producers tend to become the *L* firms in the market. Some other firms take an effective first-mover approach, since they happen to adapt quickly to the identified market spot and start making profits from the moment they step in. The long-term efficient producers have higher sunk costs, have a scale-based strategy and need more time to reach an operational point before generating positive returns.

The new findings broaden the set of conditions for which dual market structures can be expected, and hence generalize the theory of market partitioning: (i) firms can differentiate in their degree of scale advantage through their level of production capacity (sunk costs); (ii) every firm faces a balance between scale and scope economies; (iii) this balance depends on both the firms' cost structure and their location in the unimodal resource space; and (iv) firms can make use of their scale advantage through price competition.

Computer simulation results are dependent on model architecture and parameterization; so their findings do not prove, but rather may corroborate hypothesized tendencies[35]. Our findings on new aspects of dual market structure emergence indicate the possibility of such outcomes [15]. It is up to subsequent empirical investigations to identify these, or similar, outcomes in real-world markets.

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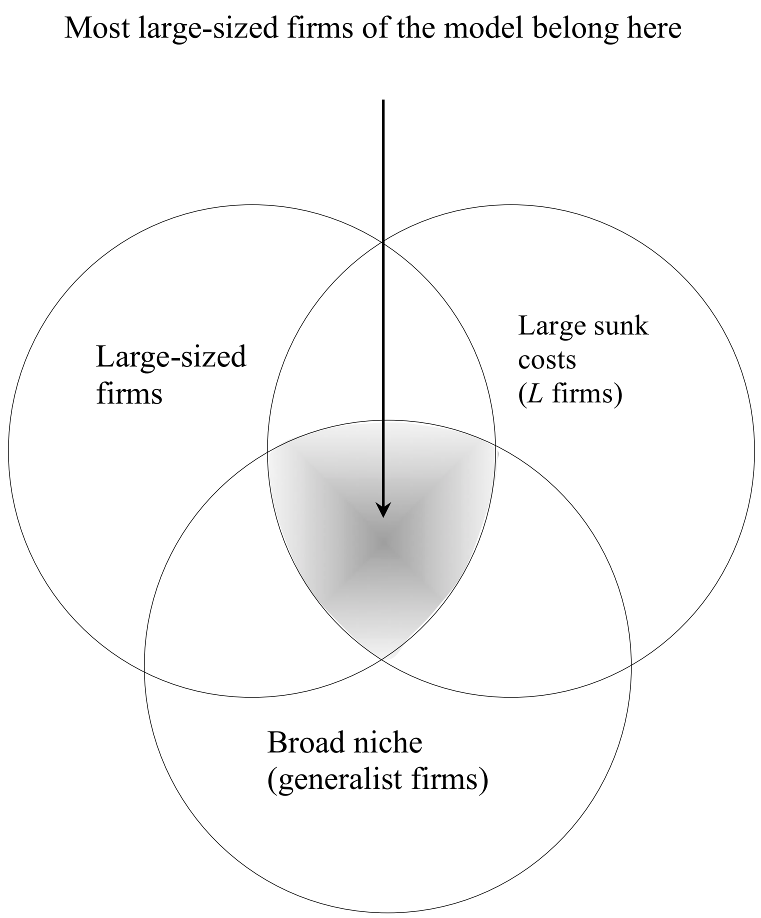
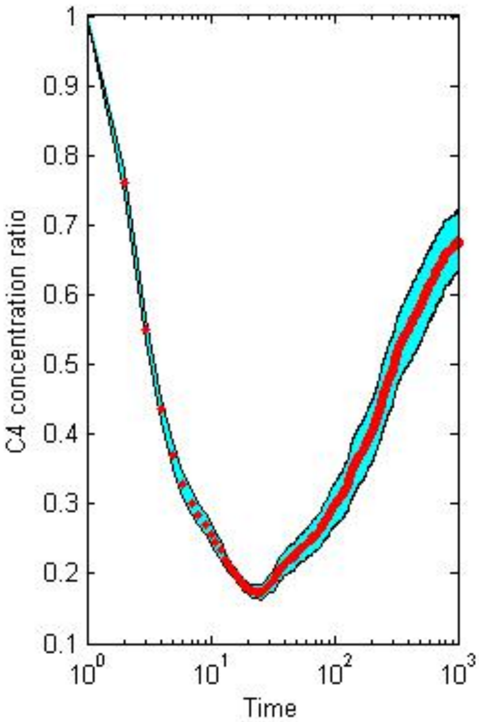


Figure 1. Correspondence between the three firm typologies

As time passes surviving *L* firms tend to be large and have a broad niche, while surviving *S* firms tend to be small and have a narrow niche.



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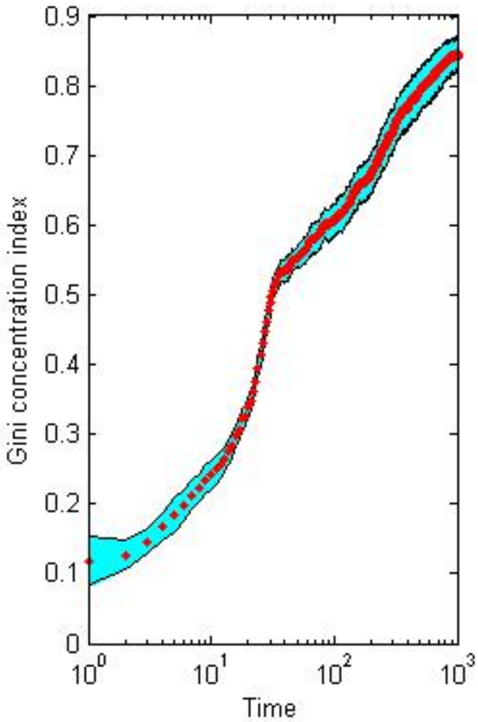

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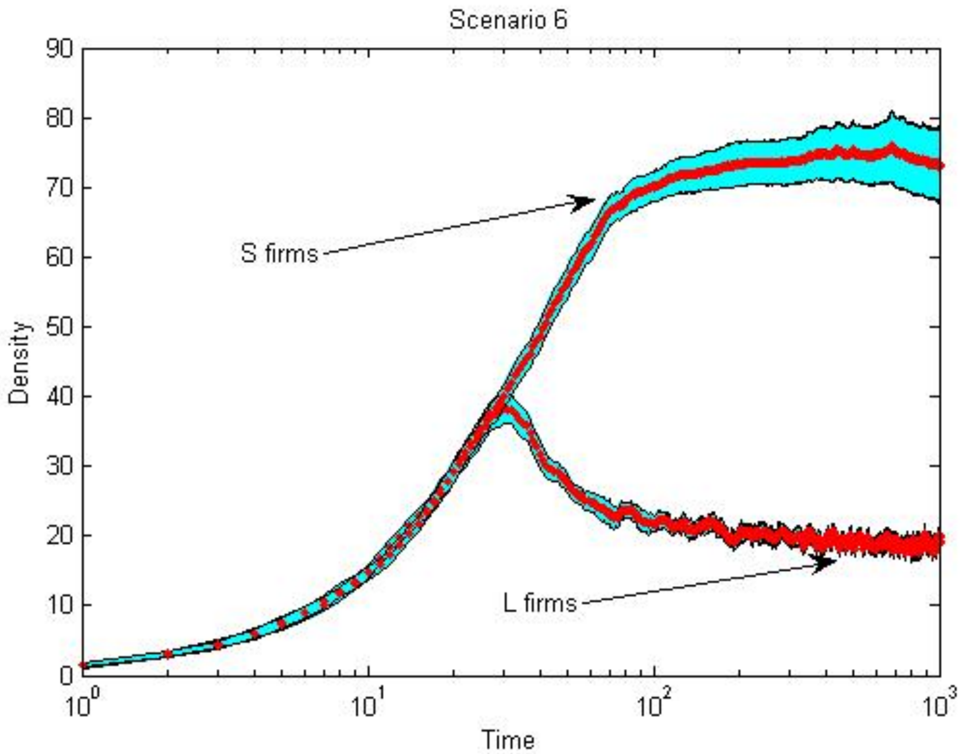


(c)

Figure 2. Average model behavior in Scenario 6 (shadowed regions correspond to confidence intervals)

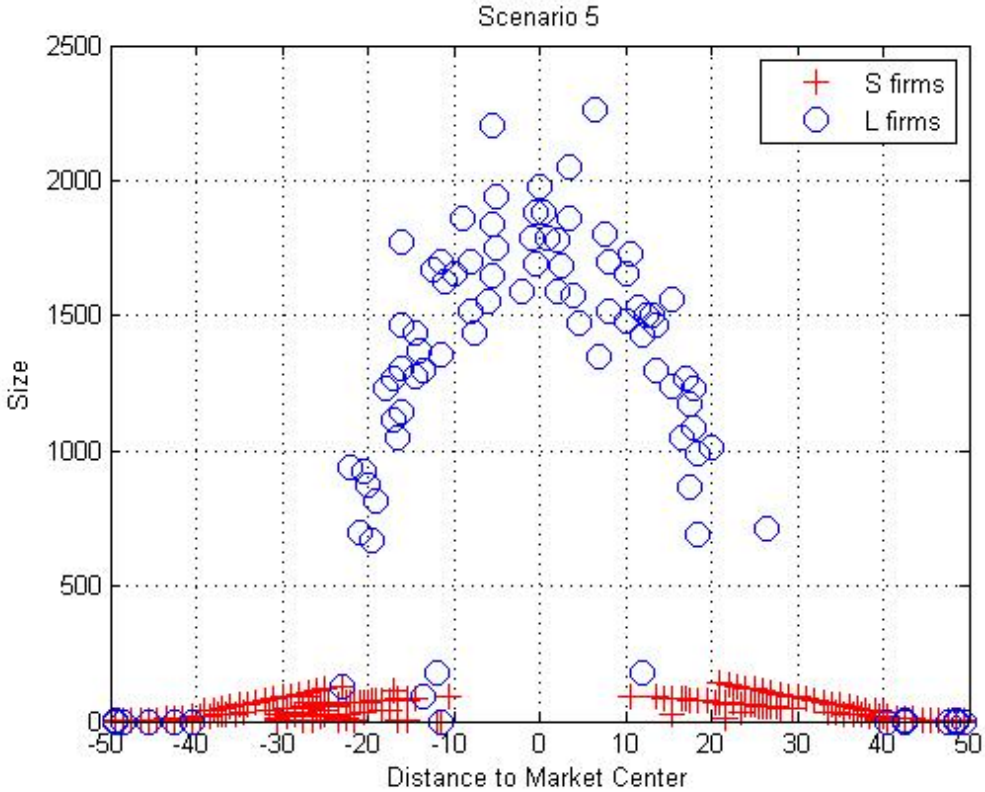
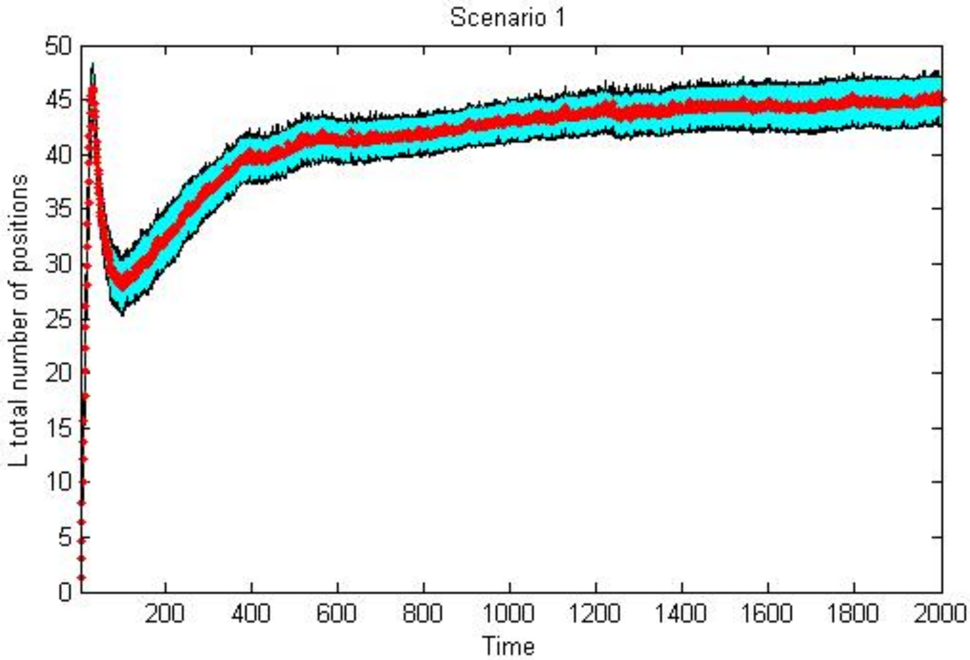


Figure 3. Size distribution per firm type (aggregated data on all simulations for this scenario)



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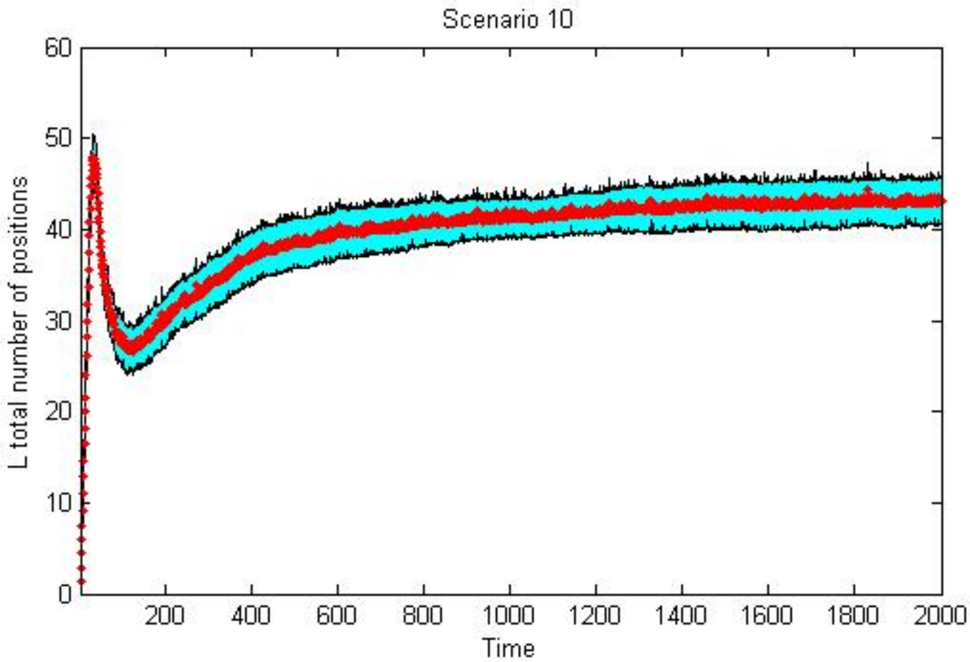
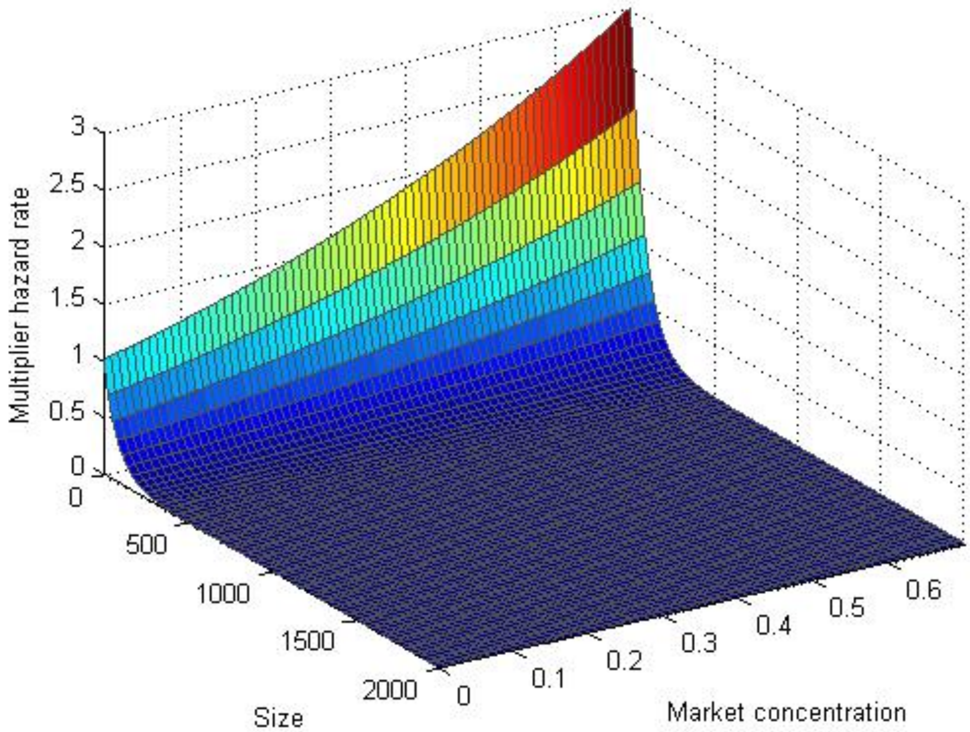


(b)

Figure 4. ***L*-firm space occupancy over time (shadowed regions correspond to confidence intervals)**



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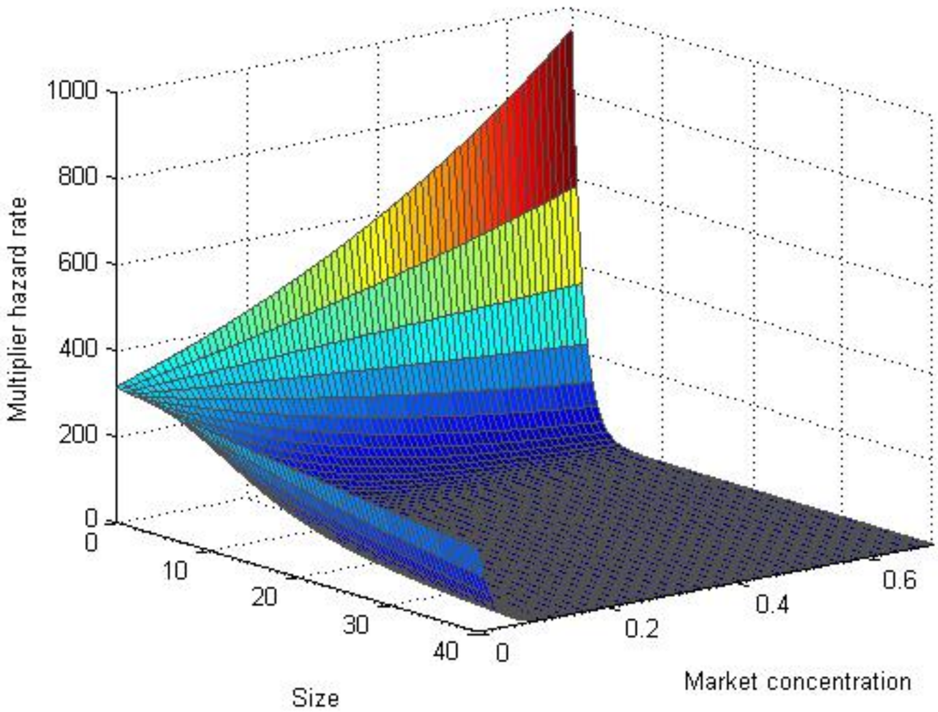

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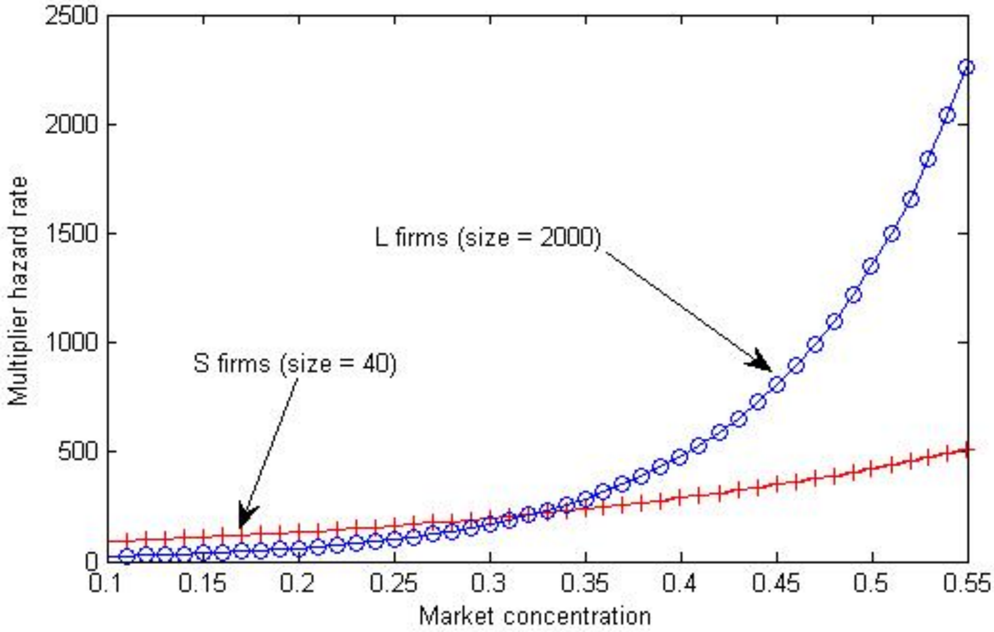
Figure 5. Dependency of mortality effects on market concentration and size for scenario 13: (a) L firms, (b) S firms



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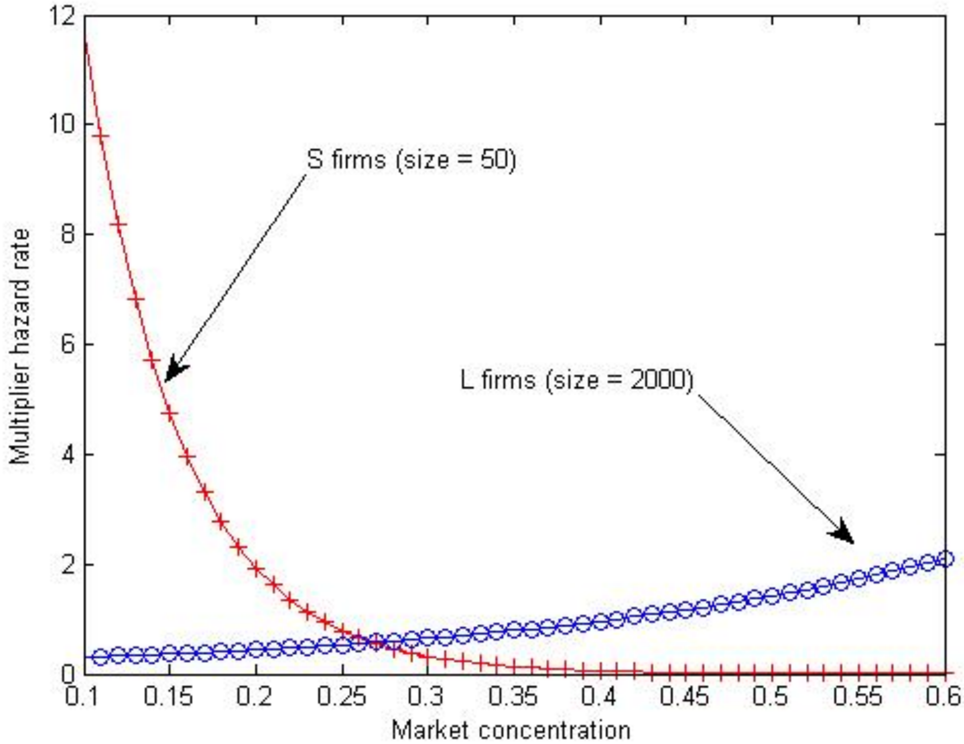

(b)

Figure 6. Mortality effects with increasing concentration per firm type: Scenarios 1 (a) and 5 (b), respectively

	Size			Gini			DC			Type		
Sc.	Coef.	% Sig.	Std .Dev	Coef.	% Sig.	Std .Dev	Coef.	% Sig.	Std .Dev	Coef.	% Sig.	Std .Dev
1	**-0.17**	100%	0.04	**4.52**	100%	2.11	**1.23**	83%	1.02	**3.88**	100%	0.33
2	**-0.20**	100%	0.05	**7.70**	100%	1.53	**0.69**	57%	1.05	**4.35**	100%	0.18
3	**-0.15**	100%	0.03	**5.39**	100%	3.31	**0.62**	70%	0.82	**3.96**	100%	0.22
4	**-0.18**	100%	0.06	**1.63**	87%	3.64	**0.02**	30%	0.48	**4.06**	100%	0.21
5	**-0.12**	100%	0.03	**6.01**	97%	2.24	**0.65**	80%	0.88	**4.01**	100%	0.26
6	**-0.20**	100%	0.05	**2.46**	97%	1.46	**0.91**	93%	0.82	**3.82**	100%	0.34
7	**-0.17**	100%	0.03	**3.21**	100%	1.20	**0.96**	93%	0.92	**3.89**	100%	0.27
8	**-0.17**	100%	0.03	**4.09**	100%	1.38	**1.18**	90%	0.51	**3.84**	100%	0.24
9	**-0.06**	100%	0.02	**1.10**	93%	0.34	**0.28**	40%	0.27	**1.72**	100%	0.02
10	**-0.16**	100%	0.03	**2.28**	100%	0.88	**0.78**	93%	0.36	**4.11**	100%	0.23
11	**-0.20**	100%	0.03	**2.60**	100%	0.89	**0.75**	87%	0.71	**3.90**	100%	0.21
12	**-0.16**	100%	0.04	**4.18**	100%	1.09	**1.44**	97%	0.69	**3.87**	100%	0.25
13	**-0.16**	100%	0.04	**4.85**	100%	1.66	**1.44**	90%	1.51	**4.02**	100%	0.26

Table 1. Survival analysis coefficients

Independent variables		Concentration (Gini) index	*L* density	*S* density	*L* space contraction
Q_S	Small sunk cost parameter	-.0175831*	-.1431061*	2.774796*	1.363785*
		(.0002214)	(.0045447)	(.0448818)	(.0217619)
γ	Product dissimilarity	-.0025169*	.0045806	.5720272*	.1815882*
		(.0001565)	(.0031975)	(.0340542)	(.0149023)
φ	Markup factor	.1163989*	-1.44986*	76.54684*	9.791984*
		(.0155546)	(.3160434)	(3.394657)	(1.464913)
ExpCoef	Expansion coefficient	3.238009*	8.51728*	-263.9791*	-121.3129*
		(.1568174)	(3.169922)	(34.50324)	(14.7435)
E	Endowment	.00345*	1.250871*	.0937271	.6340934*
		(.0002614)	(.0061466)	(.0563541)	(.0244667)
X	Entry rate	.0007879*	5.255838*	7.353022*	3.898299*
		(.0025293)	(.0516949)	(.5532305)	(.2395199)
Intercept		.8440625*	-9.539741*	-106.2712*	-39.89156*
		(.0233112)	(.4662876)	(5.094417)	(2.274647)
Number of observations		3223	3223	3223	3223
F(6, 3126)		1125.17	8786.44	801.88	784.76
R^2		0.6845	0.9545	0.5640	0.6199
Root MSE		0.07178	1.4674	15.711	6.8014

Robust standard errors in parenthesis; * $p < 0.05$.

Table 2. Regression results

Materials and Methods

Extended conceptual model description

A.1 The resource space and location specification at entry

The resource space corresponds to a unimodal distribution of consumers along a set of taste preferences of size N. Each taste preference has a number b_k of consumers, $k = 1,2, \ldots, N$. The resource space is set according to a beta distribution with parameters $\alpha^* = \beta^* = \eta$. In order to get a unimodal representation we use $\eta = 3$ and $N = 100$. Firms enter the market at a constant rate x per time period provided that the space is not completely occupied; otherwise (i.e., when the market is fully saturated) there is no entry. All the simulation runs are performed using a total demand of $\sum_k b_k = 5500$ consumers. Firms that enter the market pick up their initial location according to the probability distribution of non-served consumers, $\boldsymbol{\rho_t}$, which is given by:

$$\rho_{k,t} = \frac{(1 - CBP_{k,t-1})b_k}{\sum_{i=1}^{N}(1 - CBP_{i,t-1})b_i}, \quad \forall k = 1,2,\ldots,N, \tag{A1}$$

where $CBP_{k,t-1}$ represents the active consumer base percentage at position k at time $t-1$. Since at the beginning of the simulation (t = 0) there is no active consumer base, then $\rho_{k,0} = b_k/\sum b_i$.

A.2 Firm's cost structure

Firms have a two-piece cost function. One piece relates to the production costs $C^i_{PROD,t}$, and the other one accounts for the niche-width costs, $C^i_{NW,t}$:

$$C^i_t(Q) = C^i_{PROD,t}(Q) + C^i_{NW,t}. \tag{A2}$$

Production levels Q are quantified through a Cobb-Douglas function:

$$Q_{i,t} = F_i^{\alpha} V_{i,t}^{\ \beta}. \tag{A3}$$

Coefficients α and β correspond to production volume elasticities with respect to production factors F and V (that is, $\alpha = (\partial Q/\partial F)(F/Q)$ and $\beta = (\partial Q/\partial V)(F/Q)$). Firms derive their production costs, $C^i_{PROD,t}$, from a long-run average cost curve, $LRAC$, of the whole industry. The $LRAC$ curve is the envelope of the most efficient production possibilities in the industry. We make $\alpha + \beta > 1$ in order to reflect a downward-sloping $LRAC$ and positive scale economies. Production costs for the firm are calculated according to the usage of production factors amounts F and V that the firm needs to produce quantity Q. That is, assuming that production factor prices are W_F and W_V, respectively, the $LRAC$ curve is calculated by solving the following optimization problem:

$$\begin{aligned} \min \quad & W_F F_i + W_V V_i \\ s.t. \quad & Q_{i,t} = F_i^{\alpha} V_{i,t}^{\ \beta} \end{aligned}. \tag{A4}$$

Parameters W_V, W_F, α and β are set in order to obtain a (normalized) unit cost of 1 when $Q = \sum_i b_i$ ($W_V = 4.15$, $W_F = 2W_V$, $\alpha = \beta = 0.7$). The production cost of every firm i, $C^i_{PROD,t}$, is also computed through Equation (A4), but then assuming that the firm has a fixed usage of factor F, independent from production levels (that is, $W_F F_i$ represents firm's fixed costs). Firms may have two different alternatives to define the usage of factor F: a large (L) and a small one (S). These two options define the two different firm types in the model. Each one of the two possible values of F is set according to the quantity Q at which the firm's cost curve and the *LRAC* intersect. The model assumes that the large fixed cost indicator, Q_L, is set at least at half of the total market demand, $Q_L \geq \sum_i b_i/2$, while the small sunk cost value, Q_S, varies from quantities as low as 5, $Q_S \geq 5$. The baseline model uses $Q_L = \sum_i b_i/2$ and $Q_S = 10$. However, model's behavior is also inspected under different "scale distances" (Q_L - Q_S). An entrant has equal probability to select either firm type.

Niche-width costs represent the negative effect of covering a market with a large scope of consumer preferences. That is, a firm finds it more expensive to cover a highly diverse consumer-preference market than a homogenous one. Niche-width costs are defined as a function of the upper and lower limits of firm i's niche, and a proportionality constant *NWC*:

$$C^i_{NW,t} = NWC\left\| w^u_{i,t} - w^l_{i,t} \right\|, \tag{A5}$$

where $\|.\|$ represents the (Euclidean) distance between the two niche limits, and $w^l_{i,t}$ and $w^u_{i,t}$ represent the firm's lower and upper niche limits. Firm i's niche center is then defined as $nc^i_t = \left\| w^u_{i,t} - w^l_{i,t} \right\| / 2 + w^l_{i,t}$.

A.3 Consumer behavior

Each consumer buys only once every time period. Assuming that the selected firm has still enough produced units to cover demand, and that $S_{k,t}$ represents the set of firms that have an offer at position k, a consumer evaluates the offerings at his or her location k. The consumer buys from the firm that offers the lowest compound cost (price plus product dissimilarity) from the set of options $\{U^i_{k,t}\}$ (i.e., considering all the i-th firms that belong to the set $S_{k,t}$):

$$U^*_{k,t} = \min_{i \in S_{k,t}} \left\{ U^i_{k,t} \right\} = \min_{i \in S_{k,t}} \left\{ P^i_t + \gamma \frac{\left\| nc^i_t - k \right\|}{(N-1)} \right\}, \tag{A6}$$

where P^i_t is the firm i's price at time t, and γ is a constant that quantifies the effect of distant offerings in the space from the firm's niche center (product dissimilarity). The distance-related effect is normalized over the maximum possible Euclidean distance in the model, N - 1. In case that the selected firm does not have enough produced units to satisfy a consumer, the consumer decides to buy from the second cheapest alternative, and so on. To avoid any synchronization artifact, order positions for the buying process are randomly permuted every time period.

The reader might ask why apparently the distance effect is counted twice: firms have a negative scope effect through the niche-width cost, but also are penalized through the product dissimilarity effect. The two settings $\{\gamma > 0, NWC = 0\}$ and $\{\gamma > 0, NWC > 0\}$ produce rather similar results: Both revealed in the long run that L firms basically take over the center while S firms locate at periphery. This means that the inclusion of *NWC* does not influence the scale-based selection process of the model. However, only the setting $\{\gamma > 0, NWC > 0\}$ revealed a sharp niche-width difference between firms located at the periphery and those located at the center. Therefore, we adopt such a setting $\{\gamma > 0, NWC > 0\}$, since it resembles more precisely what resource-partitioning theory argues: Location in the space is related to the degree of niche-width differentiation (generalism / specialism).

For the sake of simplicity, we do not use demand functions, but define a limit price value for firm operations. The maximum price a consumer is willing to pay corresponds to a opportunity cost of the smallest efficient firm in the industry $P_{max} = (1+\varphi)LRAC\,|_{Q=1}$. This implies that the only reason a consumer would buy from a larger firm is that such a firm is more cost-efficient than the smallest possible firm in the industry (i.e., the firm's "scale" Q is located rightward along the *LRAC* curve). That said, consumers are allowed to bear a maximum cost U_o, so that $U^i_{k,t} \leq U_o = P_{max}$. The amount U_o defines a cost-related participation constraint for consumers. In general, if the consumer chooses to buy from a firm i^* whose niche center does not coincide with the consumer's preference k, the price $P^{i^*}_t$ has to comply with

$$P_t^{i^*} \leq P_{\max} - \gamma \frac{\left\| nc_t^i - k \right\|}{(N-1)}. \tag{A7}$$

In order to reflect scale advantages, firms use a markup price over average costs (i.e., $(1+\varphi)C(Q)/Q$), provided that the markup price complies with Equation (A7). Coefficient φ may range between 0 and 1.

We calibrated coefficients *NWC* and γ following these steps: (i) Since we assume that *L* firms are more efficient than *S* firms, we also assume that in absence of distance-related dissimilarity ($\gamma = 0$), a fully-expanded *L* firm should be able to outcompete any *S* firm. Experimentation with the model reveals that, to comply with that, the maximum value that the maximum vale the *NWC* coefficient can take is 195; (ii) with $NWC = 195$, the value range of coefficient γ was specified by assuming that the *fundamental niche* of an *L* firm (i.e., the space the firm would occupy in absence of any competition; see[36, 37]) should oscillate between half and two-thirds of the total resource space (that is, $\gamma \in [50, 70]$).

A.4 Entry price setup

Firms enter at one single position in the space. As seen in Equation (A1), we assume that firms search for a competitor-free foothold to enter the market. Firms pay attention to residual demands – the amount of non-served consumers – at different points in the resource space. From Equation (A1), we observe that the probability they step in a given location increases with the size of the residual demand spot. If the selected position for entry is position k, the firm considers a potential production quantity $Q = (1 - CBP_k)b_k$, which corresponds to the residual demand. The firm fixes a unit price that corresponds to $\min\{P_{max}, (1+\varphi)C(Q)/Q\}$.

L firms may need some time to grow and reach an operation point that allows them to sustain positive profits. S firms are able to make profits at the time they enter the market. L firms have negative profits until they reach a minimal operational point. Thus, we assume that L firms have an initial *endowment*. Endowment is implemented as a number E of periods for which a firm can survive in case of no sales (that is, covering fixed costs for E time periods). For the baseline model, E = 12, but other values are explored in order to investigate implications on the model's results.

A.5 Firm expansion

There are two possible ways for a firm to expand: vertical and horizontal. The firm uses an adaptive "rule of thumb", based on the latest information of the market, to assess if expansion is worth the investment. Being the expansion either vertical or horizontal, the firm first defines a *target quantity* in terms of the latest observed prices and costs. Based on such a quantity, the firm computes incremental profits and decides whether or not expansion is worth the investment.

(i) **Vertical expansion** refers to a niche production quantity adjustment. At time t, firm i makes production adjustments for the next round and targets the residual demand $\Delta Q_{v,t+1}$ – the amount of non-served consumers – in their current niche $H_{i,t}$, so that $\Delta Q_{v,t+1} = \sum_{k \in Hi,t}(1\text{-}CBP_{k,t})b_k$. Then, if Q_t represents firm i's latest sold quantity, the firm evaluates whether incremental revenues surpass incremental costs. If that is the case, the firm expands. Incremental costs are computed as $C^i(Q_t + \Delta Q_{v,t+1}) - C^i(Q_t)$. Incremental revenues are computed as $P^{i*}(Q_t + \Delta Q_{v,t+1})$ - $P^i_t Q_t$, where P^{i*} is calculated as follows:

$$P^{i*} = \min\left\{ P_{\max} - \gamma \frac{\left\| nc_t^i - w_{i,t}^l \right\|}{(N-1)}, (1+\varphi)C(Q_t + \Delta Q_{v,t+1}) \right\}. \tag{A8}$$

That is, firms use a markup price as long as it does not exceeds the maximum allowed price according to the width of the firm's current niche (see Equation (A8)).

(ii) **Horizontal expansion** refers to niche expansion. It also establishes a target quantity $\Delta Q^u_{h,t+1}$ and $\Delta Q^l_{h,t+1}$ on either side of the current firm's niche (upper and lower limits), respectively. The firm decides to expand toward the most attractive direction – that is, to the position where incremental profits are larger – in a similar fashion shown for vertical expansion. Firms do not always expand, so that expansion is controlled by an expansion probability, *ExpCoef*, at every time period. Values for the coefficient *ExpCoef* were jointly selected along with the time-horizon span over which we expected to see a convergence of market concentration and firm density. Since we run the model for 2000 time periods, our criteria is that an L firm should have enough time to fully expand to its fundamental niche, even if it enter the market at a mature state (> 1000 time periods). Values were chosen between 0.03 and 0.05. This coefficient might be also related to the firm's degree of inertia. Along with the results reported here, it is worth mentioning that our simulation trials confirmed a location-related selection process – L firms taking over the center and S firms dominating the periphery – even in absence of any inertia effects (i.e., *ExpCoef* = 1).

In the case a firm decides to expand, it evaluates in which direction to go. The quantities $\Delta Q^{u}_{h,t+1}$ and $\Delta Q^{l}_{h,t+1}$ are set according to the same set of rules. Let us assume that firm *i* attempts expansion to the position adjacent to its upper niche limit, *z*. If the targeted position *z* is empty, then $\Delta Q^{u}_{h,t+1} = b_z$. If some firms are already at position *z*, then the expanding firm *i* estimates $\Delta Q^{u}_{h,t+1}$ by taking into account the rival's costs $U^{j}_{z,t}$, and rivals' latest sold quantities, at position *z*, which firm *i* assumes to be the best estimates of their next time-period quantities. Then, the offered costs are compared and ranked, and the quantity $\Delta Q^{u}_{h,t+1}$ is subsequently extracted according to the relative rank the firm gets in comparison with the rivals' costs. An example of how this is carried out follows next. Let us assume that the location of interest has a total demand of ten consumers, and the compound costs at that position from two different firms are $U(A) = 10$ and $U(B) = 15$ with captured demands $Q(A) = 7$ and $Q(B) = 3$. If firm *C* attempts to enter that position, and assuming that $U(C) = 12$, the ascendant cost ranking will place firms in the following order: *A*, *C*, and *B*. Firm *C* estimates that *A* will keep its last demand in the next round (i.e., $Q(A) = 7$), since *A* still has the cheapest offer. But now, given that *C* has a better offer than *B*, *C* will steal B's demand and estimate that in the next round $Q'(C) = 3$ and $Q'(B) = 0$. Once the target quantity has been established for *z*, the firm calculates its potential incremental profits by taking into account (i) the resulting total costs with the added target, (ii) the resulting price, including the new distance compensation $\gamma \left\| nc^{i}_{(Hi,t)+z} - z \right\| / (N-1)$, where $nc^{i}_{Hi,t+z}$ is the new niche center that would result if *z* is included in firm *i*'s niche, $H_{i,t}$, and (ii) the firm's latest price and costs. The firm then computes incremental profits and performs the same calculation when expansion is attempted to the cell adjacent to the lower limit. After comparing the two incremental profits, the firm decides to expand toward the position that reveals the highest value, if any.

A.6. Analysis

We study the effect on hazard rates according to different representative scenarios, which are set according to variations in small sunk cost investment (Q_S), product dissimilarity coefficient (γ), endowment (E), entry rate (X), markup value (φ) and expansion probability (*ExpCoef*). The scenarios correspond to a model with mid-range parameters (scenario 1), variations in the small sunk cost investment (scenarios 2, 3 and 4), markup (scenarios 5 and 6), product dissimilarity (scenarios 7 and 8), endowment (models 9 and 10), probability of expansion (scenarios 11 and 12) and entry rate (scenario 13). Every scenario is run for 2000 time periods. Within every scenario, we also studied the behavior of main time-evolving variables of interest (i.e., market concentration, per-type density and per-type total covered space). Every scenario is run 30 times in order to guarantee the normality assumption of confidence intervals of such variables. We find survival analysis estimators for each realization of the 30 x 13 = 390 simulations. See Table A1 for details.

Parameter	Definition	1	2	3	4	5	6	7	8	9	10	11	12	13
Q_{SS}	Small sunk cost	10	**5**	**15**	**20**	10	10	10	10	10	10	10	10	10
φ	Markup	0.2	0.2	0.2	0.2	**0.1**	**0.3**	0.2	0.2	0.2	0.2	0.2	0.2	0.2
γ	Product dissimilarity	60	60	60	60	60	60	**50**	**70**	60	60	60	60	60
E	Endowment	12	12	12	12	12	12	12	12	**6**	**18**	12	12	12
ExpCoef	Expansion probability	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	**0.03**	**0.05**	0.04
x	Entry rate	3	3	3	3	3	3	3	3	3	3	3	3	**2**

Table A1. Parameter values for model dynamics analysis

The second analysis consists of exploring effects in four specified outcomes: market concentration, *L* firm density, *S* firm density, and *L* firm space contraction. Space contraction is evaluated as the difference between the peak space occupation and the average occupation at the final time steps of the simulation. Effects are explored with respect to variations in the simulation key parameters: small sunk cost (Q_S), product dissimilarity (γ), markup (φ), endowment (E), Expansion probability (*ExpCoef*), and entry rate (x). Using the selected values presented in Table A2, we get 4 x 3^4 x 2 = 648 combinations for the above-mentioned parameters, respectively. We build an OLS regression model using the below-mentioned parameters as independent variables, using the earlier mentioned four outcomes of interest

Parameter	Definition	Selected values
Q_{SS}	Small sunk cost parameter	5, 10, 15, 20
γ	Product dissimilarity	50, 60, 70
φ	Markup factor	0.1, 0.2, 0.3
ExpCoef	Expansion coefficient	0.03, 0.04, 0.05
E	Endowment	6, 12, 18
x	Entry rate	2,3

Table A2. Parameter values for OLS analysis

Every parameter combination was replicated m = 5 times. Thus, the total number of observations in this analysis is 648 x 5 = 3240. To guarantee more precise effects on convergence conditions, we run each simulation for 5000 time periods, and take averages on the last 500 periods on the key outcome variables (i.e., the last 10% fraction of the total simulation time).