ISSN 1980-5411 (On-line version)
Production, 34, e20230092, 2024
DOI: 10.1590/0103-6513.20230092

Research Article

Simulating continuance and resilience: an agent-based model for nanostores operations

Agatha Clarice da Silva-Ovando[a,b*], Gonzalo Mejía[b], Christopher Mejía-Argueta[c], Daniela Granados Rivera[b,d], Dayana Nicol Yugar Quiroz[a], Mario Chong[e]

[a]Universidad Privada Boliviana, Cochabamba, Cochabamba, Bolivia
[b]Universidad de La Sabana, Chia, Colombia
[c]Massachusetts Institute of Technology, Cambridge, MA, United States
[d]Auburn University, Auburn, AL, United States
[e]Universidad del Pacifico, Lima, Peru
*agathadasilva@upb.edu

Abstract

Paper aims: This study investigates the nanostores' endurance in serving underserved regions in developing countries. The research explores how various competing retail formats influence market choice and demand. We used data from a survey conducted in Sabana Centro, Colombia, in this study.

Originality: We believe this is the first study examining the nanostores' resilience in serving emerging markets under this novel hybrid technique.

Research method: We propose a multi-agent-based model mimicking nanostore survival and resilience in a competitive market. Household agents use a discrete choice model to select their preferred retail format for household purchases based on location, price, and service levels. Considering supply breakdowns, we tested the outcoming model under different disruption scenarios.

Main findings: Results indicated nanostores' great resiliency in competitive markets, specifically in peripheral areas, which are usually neglected by other retail formats. This suggests that this retail format can strategically complement household supply in underserved areas, displaying the importance of supporting these channels and generating tools that improve their performance in the market.

Implications for theory and practice: Theoretically, we aim to improve the understanding of households' decision-making process when buying food. Practically, a multi-agent-based model simulating end customers and sellers offers insights into future interventions and their impacts on the retail landscape and various supply chain stakeholders.

Keywords
Supply chain management. Facility location. Nested logit model. Multi-agent simulation. Urban logistics.

How to cite this article: Silva-Ovando, A. C., Mejía, G., Mejía-Argueta, C., Granados Rivera, D., Yugar Quiroz, D. N., & Chong, M. (2024). Simulating continuance and resilience: an agent-based model for nanostores operations. *Production*, *34*, e20230092. https://doi.org/10.1590/0103-6513.20230092.

Received: Nov. 25, 2023; Accepted: Aug. 29, 2024.

1. Introduction

In urban and densely populated areas of emerging countries, the food retail landscape shows a growing diversity of formats characterized by retailers that vary in size, assortment, business models, and operations (Fransoo et al., 2017). This diversity of retail formats empowers consumers with multiple alternatives, enabling them to make informed choices by comparing various purchase options. Conversely, city areas with lower population densities situated farther from central urban hubs typically have fewer larger, modern retail channels (Silva-Ovando et al., 2021).

Consequently, the communities living semi-urban areas of emerging countries compelled to bear higher costs when acquiring food due to increased commuting expenses or the necessity to patronize local markets. The economic hindering effects from limited economies of scale and inefficient supply chain (SC) operations in these local markets often result in elevated prices for locals (Cummins et al., 2010; Escamilla et al., 2021; Food and Agriculture Organization, 2022). Consequently, these residents struggle to afford well-assorted food points of sale and have broad access to unhealthy dietary choices, which are easier to manage but can adversely impact meal quality and the nutrition of communities (Levi et al., 2020).

To address this challenge, small, traditional, family-owned retailers, commonly referred to as nanostores (e.g., corner shops and convenience stores), have a significant presence in underserved peri urban environments (Fransoo et al., 2017; Mejía-Argueta et al., 2019a; Silva-Ovando et al., 2021). Nanostores are characterized by their convenience and providing access to essential consumer-packaged goods (CPGs) and fresher goods (Fransoo, 2021). The establishment of nanostores in urban and suburban regions play a pivotal role in ensuring food accessibility for households that encounter difficulties in traveling to more distant, larger retail channels (Paswan et al., 2010). In Colombia for example, over 500,000 nanostores are present in all regions of the country. Their market share exceeds 48% of the total sales of food according to the Colombian Federation of Trade (Fenalco, 2022). However, their limited financial resources, and often poor management, make them vulnerable to disruptions in the supply chain as we witnessed with the COVID 19 pandemic (Cajamarca, 2022). Despite their importance, the resilience of nanostores is a topic that has been little investigated.

This paper explores the resilience and endurance of nanostores in emerging countries in the face of disruptive scenarios. The following research question is posed:

RQ1: What are the disruptive factors in the supply chain that affect the survival of nanostores?

In this research, a multi-agent simulation model is proposed to answer this question. This approach studies how disruptive events affect households' retail preferences, considering variables such as travel distance, pricing considerations, and service levels. Our approach capitalizes on the collection of primary and secondary data sources and combines simulation and discrete choice models to investigate how the nanostores' features and resilience under disruptions may impact the whole food ecosystem regarding coverage. Our approach presents an agent-based simulation to model the channel choice and amounts to serve orders by considering a periodic base-stock policy. The innovative aspect of this approach lies in the application of multi-agent systems to study how disruptions can influence the dynamics of food retail landscapes, particularly in emerging economies.

The contribution of this work relies on building knowledge on the decision-making process for end costumers to buy fresh food, generating a connection between consumer choices and retailer's location using a nested logit approach, and approaching an understanding of the roles of nanostores under disruptive scenarios. Practically, we address the vulnerabilities on nano retail operations in emerging economies.

This paper is organized as follows: section 2 presents the literature review used in this study. A description of the study case applied in Sabana Centro-Colombia is provided in Section 3. Then, Section 4 presents a brief methodological background of the multi-agent simulation and the discrete choice models, as well as the data collection and the multi-agent-based model, which are described in this section. Section 5 analyzes and discusses the results of the experiments, and Section 6 provides the main conclusions of this research.

2. Literature review

2.1. Food retail landscapes in emerging market economies

A food retail landscape refers to the variety and distribution of places where food is sold to consumers. This includes different types of retail establishments and their geographic arrangement within a specific area or community (Swinburn et al., 2013). Various retail formats emerge in this expansive landscape of food environments, from digital platforms to traditional brick-and-mortar establishments (Boulaksil et al., 2019).

Additionally, it has been evidenced that consumers are now shopping more often and at a wider variety of stores. Many only plan a few meals ahead, leading to frequent, smaller shopping trips. Furthermore, they often combine grocery shopping with other activities like commuting, leisure, or education, making their shopping patterns more complex (Sturley et al., 2018). In this direction, the proximity to diverse retail formats substantially shapes the availability of food, its assortment, and price, which drive consumers' purchasing trends (Salinas-Navarro et al., 2024).

Although some works have been reported on the efficiency of traditional retailers in peripheral regions (Fransoo et al., 2017; Mejía-Argueta et al., 2019a; Escamilla et al., 2021), the resilience of these nanostores over time has been little studied. A few studies have looked at the survival angle of nanostores and their effect on supply chains without addressing the household choice component (Mejia Argueta et al., 2019b; Mora-Quiñones et al., 2021).

Existing research has explored various dimensions of supply chain optimization, ranging from storage processes (Moyano et al., 2022) to demand and order management for nanostores (Fransoo et al., 2017; Ge et al., 2021) and addressing last-mile uncertainties (Boulaksil & Belkora, 2017). Many other approaches often focus on improving the supply process efficiency from the supplier's perspective (Brown & Guiffrida, 2017; Kin et al., 2018; Gutiérrez-Rubiano et al., 2019; Kin, 2020; Brown et al., 2021). On the same line, other approaches include establishing facilities to improve the manufacturer's last-mile delivery process (Awasthi et al., 2011; Freitas & Domingues, 2013; Sopha et al., 2016). A few evaluate how those decisions would impact the nanostore process mid to long-term (Mejia Argueta et al., 2019a). Moreover, none of the current proposals assess the role of nanostores in optimizing and ensuring a reliable food assortment for underserved regions.

2.2. Evaluating resilience performance through agent-based models (ABM)

Specifically in retail, most of the ABM approaches focus on customer behavior. For example, Torrens (2023) explored customers' behavior and dynamics and how they affect their purchase behavior. This approach is customer-centric and measures no effects caused by retail-related decisions. Similarly, Zhang & Robinson (2022) applied ABM to study location allocation problems. Finally, Sturley et al. (2018) abstracted the consumer's retailer choice through ABM. This study considered geolocation factors and found distance and shopping frequency relevant to the decision process, similar to our study. However, Sturley evaluates the capability of ABMs to model and replicate individual consumer behaviors that influence store and channel selection, shopping frequency, shopping purpose, and expenditure.

Generally, ABM applied to food systems is scarce in the literature. Among the few food systems that have been modeled with ABM, Calisti et al. (2019) studied how the location of farmer markets can impact the food environment in Italy. Conversely, Widener et al. (2012) studied the impact of supermarket entry in Buffalo (USA) areas on food intake. Later, Mejía & García-Díaz (2018) investigated the topic of intermediation of the fresh potato supply chain in Colombia through ABM simulation and Q-learning. Later, Zissis et al. (2018) studied a collaborative distribution system for online grocery shopping with a combination of math modeling and discrete event simulation.

Literature is even scarcer when looking for general studies in retail resilience. Larrea-Gallegos et al. (2022) carried out a review seeking applications to model supply chain resilience. Most applications consider the whole supply chain network in their study, from the first to the last mile. Usually, producers and intermediaries are the "active" agents, determining their actions on the supply chain as demand shifts (van Voorn et al., 2020; Shaaban et al., 2023). At the same time, none of the retailers are considered relevant decision-makers in the chain. In our study, nanostores represent an active agent in the simulation, and decide on their supply process.

2.3. Research gaps

First, ABM applications for food retail operations in emerging regions are scarce. Emerging markets are undergoing a transformation in retail due to rapid urbanization. While multinational retailers have established a presence over the past few decades, traditional retail channels, consisting of numerous small stores (or nanostores), continue to prevail. Recent evidence indicates that these traditional small-store retailers will remain a significant part of the retail landscape for the foreseeable future (Fransoo et al., 2017). Second, when studying resilience in food supply chains (FSC), most studies approach the whole chain, focusing significantly on producers and intermediaries. Thus, his study aims to model and analyze how the responses of specific retailers (such as nanostores) are affected by disruptive scenarios.

Practically, few applications considered emerging countries or regions, which have different dynamics on their supply chains from more developed nations. Their limitations and fragmentations are factors that can add value to understanding critical factors, such as resilience.

3. Case study: Sabana Centro, Colombia

The study area for this paper is the suburban Sabana Central region in the province of Cundinamarca, Colombia. We chose this location due to the availability of data and the various sources of supply. Located in the north of Bogotá, the capital of Colombia, Sabana Centro consists of 11 municipalities (Sabana Centro Cómovamos, 2017). By 2022 Sabana Central population was 607,238 people (Colombia, 2022), representing around 18.7% of the total population in Cundinamarca. By 2020, the urban population in Sabana Central accounted for 69%, which is expected to rise to 74% by 2026. The highest population density is concentrated in the towns of Chía and Cajicá, which has increased over 50% recently. By 2020, Chía's population density was 1,968 residents/km^2, while Cajicá had 1,754 residents/km^2 (Sabana Centro Cómovamos, 2021).

Sabana Central is well known for its agricultural operations (Sabana Centro Cómovamos, 2021). However, the primary sector (agricultural activities) accounted for only 2.6% of the aggregated value generated in the region. Conversely, the tertiary sector (retail products and services) accounted for around 52.8%. These municipalities represent emerging countries in Latin America, with high urbanization distributed in urban and peri-urban regions, commercial fragmentations, food accessibility, and affordability challenges. Therefore, we consider that these regions provide diversity to the study. Accordingly, Figure 1 presents the two towns, Chía (purple) and Cajicá (green).

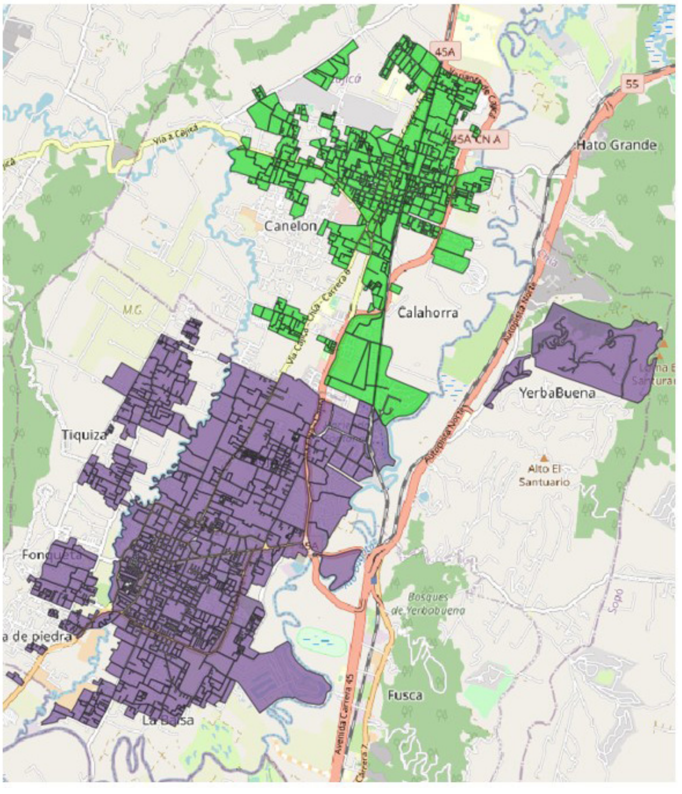

Figure 1. Municipalities of Chía and Cajicá (Scale 1:74961).

Small supermarkets and nanostores (corner shops) primarily characterize Chía and Cajicá's retail landscape. Although supermarkets and fruvers (typical markets in Colombia, specializing in fresh food retail (Constanza Gómez, 2005)) are present in densely inhabited areas, they fail to serve communities in peripheral and rural areas (Silva-Ovando et al., 2021). Our proposed methodology explores ABM to predict how the nanostores are affected by supply disruptions.

4. Materials and methods

The proposed approach includes the development and calibration of an ABM to simulate households' shopping behavior by running computational experiments, including sensitivity and scenario analyses. We first present the theoretical framework and each step of the methodology applied in this section.

4.1. Theoretical framework

4.1.1. Discrete choice models

Discrete choice models are regularly used in many contexts where agents choose among several alternatives. Each agent perceives a utility for each of its choices depending on attributes associated with preferences (i.e., weights) (Train, 2009) and chooses the one that provides the highest value. Discrete choice models are popular for describing the factors that affect food purchase and intake (Nogueira et al., 2018).

We use the nested logit model (NLM) because it functions considering a potential correlation among alternatives (Train, 2009), which are ultimately clustered into a nest. The correlation means that, on a first level, the utilities of any existing alternative within a nest are composed of a conjoint utility (referred to the nest) and an independent utility (referred to the choice itself). In the NLM, the utility is given by $U_{hi} = V_{hi} + \varepsilon_{hi}$, where V_{hi} is the utility observed of decision maker h of alternative i and ε_{hi} is a random unobserved term. The observed value of the utility can be expressed in its simplest form as a weighted sum of L factors as follows: $V_{hi} = \beta_{0i} + \beta_1 X_{1i} + \beta_2 X_{2i} \ldots + \beta_l X_{li} \ldots + \beta_L X_{Li}$, where X_{li} is the stated value of the l^{th} factor evaluated for the alternative i, and β_{li} indicates the individual weight perceived for each factor. This basic model suffers from the widely known independence of irrelevant alternatives. This occurs when the decision maker is faced with alternatives that are very similar, potentially leading to indifference between the options, or when the choice probabilities are artificially inflated. The remedy is to group similar alternatives in K "nests". Let B_k be the k-th nest that includes one or more alternatives. It is assumed that for any two alternatives i and i' in nest B_k, then term ε_{hi} is correlated to $\varepsilon_{hi'}$. Equation 1 presents the choice probability P_{hi} for alternative $i \in B_k$.

$$P_{hi} = \frac{e^{V_{hi}/\theta_k} \left(\sum_{i' \in B_k} e^{V_{hi'}/\theta_k} \right)^{\theta_k - 1}}{\sum_{l=1}^{K} \left(\sum_{i' \in B_l} e^{V_{hi'}/\theta_l} \right)^{\theta_l}} \quad (1)$$

The parameter $\theta_k, 0 \le \theta_k \le 1$, measures the degree of independence in the unobserved utility among all the alternatives contained in the nest k. The higher the value of θ_k, the higher the independence level among the utilities. As in the β values, the θ_k parameters are calculated with numerical methods based on collected data.

4.1.2. Agent-based modelling

An ABM is proposed to study the network's dynamics to provide a comprehensive evaluation of the feasibility of specific interventions, present their effects on other stakeholders from a high-level perspective, and facilitate the analysis of different scenarios (Macal & North, 2007). Typically, an ABM comprises:

1. *Evaluate the status of the agent and its environment*: The agent determines the conditions to act according to their current scenario;
2. *Decide*: An agent acts depending on its status, the environment, and objectives. The decisions range from simple rules (e.g., if…then… else) to complicated reasoning procedures;
3. *Evaluate the decision*: Agents update their status and assess the impact of their decision.

4.2. Data collection

4.2.1. Primary and secondary data collected from households

This study was based on two surveys carried out by Universidad de la Sabana and the Special Administrative and Planning of the Central Region (RAP-E). The first survey was conducted on households and the second on managers of fruvers and nanostores. Around 500 surveys were conducted "in situ" on households in Chía and Cajicá. The survey contained 85 questions concerning socioeconomic factors and purchasing habits of 10 food groups defined for the Colombian basic food basket. It aimed to find patterns in household consumption, perceived food contexts, and food choices according to societal backgrounds.

Silva-Ovando et al. (2021), performed a first approach to the information generated by this survey, where authors identified the patterns of retail landscape in the region. The second survey, also conducted "in situ", included questions on supply channels, purchasing quantities and frequencies, and patronage.

Given that the survey was conducted using a stratified sample of the region, the chosen households' locations accurately represent the area. We used this data to extrapolate potential demand based on the geolocation of the surveyed households. Information from DANE allowed us to determine the population density and the area of the blocks where these households are situated. Assuming an average of four inhabitants per household, we extrapolated the potential household demand for each block. We termed this extrapolated household demand as a "demand block" or "household block" and assigned this demand value to the surveyed households as a reference. Equation 2 illustrates the calculation used for this demand extrapolation.

$$\frac{demand\ in\ kg}{household - week} \times \frac{\#\ inhab}{m^2} \times \frac{1\ household}{4\ inhab} \times block\ area\ in\ m^2 = kg / week \tag{2}$$

Data from the National Statistical Institute of Colombia (DANE) and RAP-E were secondary sources. DANE provided geo-located data and socioeconomic levels. Accordingly, RAP-E- assisted in designing the survey (e.g., type, sample size, randomized sampling methods, and localizing geographical data). This approach allowed the households' location, socioeconomic status, size, purchase behavior, and average demand.

4.2.2. Primary and secondary data collected from retailers

The geographical locations of supermarkets, fruvers, nanostores, and other retailers were established with Google Maps™. in the towns of Chía and Cajicá. We geo-referenced 41 supermarkets (between Chain supermarkets, hard-discounters, and convenience markets), 60 fruvers, and 89 nanostores in both municipalities (See Figure 2). Nanostores were found mainly in suburban areas, with scarce coverage of other retailers.

The household survey conveyed information as to the coverage for each retailer in the region, presenting the households' retail format preferences. We considered the average price per kilogram of the most demanded products in the food basket, according to our surveys. Table 1 presents the resulting data.

Table 1. Average prices in US$ per kilogram of food (US$/ kg).

Parameters	Market Plaza (Corabastos)	Nanostores	Fruvers	Supermarkets
Average	0.5	0.96	1.05	0.94

The distances between sellers and buyers were estimated by introducing the locations found through Google Maps™ into QGis 3.16 and generating a distance matrix connecting each pair origin-destination.

4.3. The ABM

The general structure for ABM models requires rules (purchase decisions), agents (households, nanostores, and competitors, and wholesalers), and environment (market interaction) (Shoukat & Moghadas, 2020). Further, all agents must be heterogeneous, because each agent represents a unique element in the model. In this case, heterogeneity is given from each agent's capacities, location, and demand. The demand from the household is the first input that generates all the interactions and decisions in the environment. The dynamics of this model are generated by the changes in the environment. For example, nanostores can go inactive at any point, or present limited supply capacity, changing the market dynamics. The demand behavior and the impact size are randomized from the parameters found in data collection.

This section describes the ABM's elements, assumptions, and pseudocode. In this simulation, decision-makers (households and nanostores) consider two decisions: (1) determine the order quantity and (2) decide the specific seller to buy from. The first decision concerns inventory management, considering space and perishability in ABM.

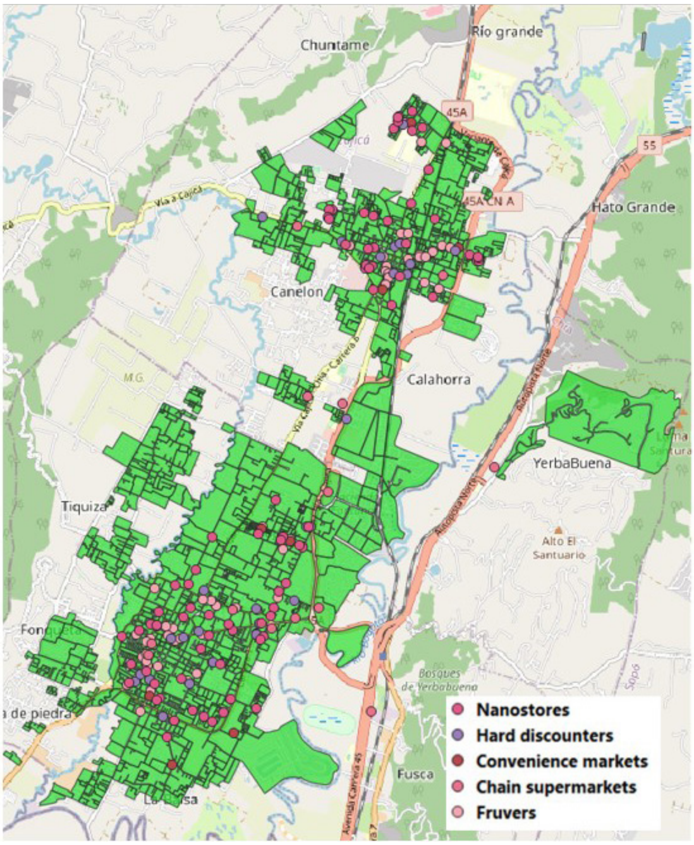

Figure 2. Food landscape in Chía and Cajicá (Scale 1:74961) (Silva-Ovando et al., 2021).

The second decision uses a discrete choice model (Train, 2009), considering primarily accessibility and affordability (i.e., price, distance, and availability). The objective was to evaluate how the food retail landscape would respond to supply chain disruptions.

- Model's assumptions.
  - Number of runs: The length of the run was set at 1,000 days;
  - Warm up time: 50 days;
  - Number of replicas: 100, as suggested by Ritter et al. (2011);
  - The model contemplates various disruptive scenarios, which will take place randomly during the runs;
  - If a household cannot fulfill its demand in a nanostore, it is assumed that they will not visit another retailer to purchase.

4.3.1. Agents

This study considered active and passive agents. We coined passive agents to distinguish these entities from the term "environment" (typically used in the literature) because they also operate as decision-making entities in real life.

In this study, we propose two active agents: households and nanostores. Active agents make two purchase decisions, namely, market choice and order quantities. Passive agents only sell their products to active agents 8and keep their stock updated, abstaining from decision-making. Fruvers, wholesalers and supermarkets are passive agents.

- Assumptions for households.

- Number of household agents: 500. These correspond to approximately the number of blocks in the two towns;
- Food demand: the daily demand was based on the households' declared demand in the survey. Each household data was extrapolated to the number of households in the block where they were located. We assumed a family size of four and food loss and waste of 25%;
- Order quantities: household agents use a base-stock model. Thus, the order quantity at a given period corresponds to the last cycle demand. The shopping frequency was randomly generated from the empirical probability distribution of frequencies obtained from the surveys;
- Market choice: Households may shop from any channel per purchase within a maximum walking distance arbitrarily set to 500m (0.3 miles).

- Assumptions for nanostores.
  - Number of nanostores agents: 89, located with georeferenced tools;
  - Nanostores' demand: the daily demand was calculated from the nanostores' patrons order quantities;
  - Shopping frequency: randomly generated from the empirical probability distribution of frequencies obtained from the surveys;
  - Order Quantities: nanostores also use a base stock model, where the order quantity corresponds to the last cycle demand;
  - Market choice: nanostores only shop from wholesalers;
  - Costs: nanostores owners have a fixed operation approximately US$1200, according to nanostores owners in the region. We considered that nanostores will offer other products than fruits and vegetables. Thus, we defined that fresh food should cover at most US$700 of the total operational costs.

- Assumptions for other channels.
  - Number of agents: two wholesalers, 41 supermarkets, and 60 fruvers;
  - Food demand: calculated based on order quantities of their patronage;
  - Food availability: all other channels have an unlimited food supply.

4.3.2. Disruptive scenarios generation

To evaluate the nanostores' resilience and their capacity to serve their patronage under disruption events, we proposed analyzing the effects of several events based on their impact and their likelihood to happen.

We considered data from the disruption caused by the COVID-19 pandemic, where around 80% of producers presented difficulties transporting their goods to the markets (Rios Monroy, 2020). Likewise, food retailers experienced about 87% reduced supply (United Nations, 2020). Thus, we considered a maximum supply impact of 80% appropriate. For convenience, we assumed that all scenarios had equal occurrence probability (see Table 2).

Table 2. Impact variations.

Events	Impact	Probability
Baseline	0%	
Low impact	10%	25%
Medium impact	25%	25%
High impact	50%	25%
Very high impact	80%	25%

The average time between disruptions is called Mean Time to Disruption (MTTD), while the average duration of the event is referred to as Mean Duration of Event (MDOE). Both values were defined according to percentual impacts perceived in previous disruptions in the region. To generate the random numbers, we used the inverse of the cumulative exponential function, given by $\ln\left(1-U\left(0,1\right)\right)\lambda$, where λ is mean time for an occurrence and U(0,1) is a random number between 0 and 1 drawn from an uniform distribution (Sturley et al., 2018).

The baseline scenario presented no disruptions. To generate MTTD, two values of λ were selected. Likewise, the two values of MDOE were defined. The λ values were selected to generate different patterns of disruptions in the region, because their objective is to identify the changes in the households' choices and its effects on the food landscape and detect the regions where the nanostores have better resilience, these being strategic to attend an underserved demand. The model selected random values from Table 2 to determine the impact of each occurrence. Table 3 provides a summary of the scenarios formed.

Table 3. Scenarios.

Scenario	MTTD (days)	**MDOE** (days)
Baseline (Scenario 0)	0	0
Scenario 1	50	50
Scenario 2	50	100
Scenario 3	100	50
Scenario 4	100	100

If two events overlap during the simulation, the impact size are totaled on the overlapping days.

4.3.3. Model pseudocode

Table 4 presents this model's sets and parameters. Table 5 displays the decision variables.

Table 4. Definition of sets and parameters.

Sets	
H	Households
I	Nanostores
SU	Supermarkets
F	Fruvers
WH	Wholesalers
$S = I\,SU \cup F \cup WH$	Set of sellers indexed by s.
$B = (N \cup H)$	Set of buyers indexed by b. Nanostores are both sellers and buyers.
$A = S \cup B$	Set of all agents indexed by a.
$\mathcal{T}$	Set of periods (days).
SD_b	Subset of shopping days of buyer b.
PS_{bt}	Subset of potential sellers for buyer b on day t. These are those that are open on day t and within withing a maximum distance from buyer b.
Parameters	
T'	Number of simulation days.
δ_{ht}	Household h daily demand on day t.
$T(a)$	Review period of agent a.
μ_h	Average daily demand of household h.
σ_h	Standard deviation of daily demand from household h.
I_{b0}	Initial stock of buyer b.
p_s	Sale price of seller s.
f_i	Fixed cost of operation of nanostore i during a 90 day period
C	Unit cost at wholesaler's facility.
np_i	Net profit of nanostore i
d_{bs}	Distance between buyer b and seller s.

Table 5. Decision variables.

Decision Variables	
q'_{ht}	Order quantity of household h on day t.
Q_{ii}	Quantity purchased by buyer b from seller s on day t.
I_{bt}	Stock of buyer b on day t.
sl_{st}	Service level of seller s This stockout ratio up to date t
Δ_{it}	Cumulative demand of nanostore i up to day t. This is the cumulative purchases at nanostore i from households up to day t.

The execution of the simulation is the following: first, nanostores review their stocks and define their purchase quantity. Then, these agents purchase from the nearest wholesaler their demand according to a periodic base-stock policy (R, T) with lost sales. Finally, nanostores sell their products to households, competing with other channels. Similarly, households review their stocks according to their purchase frequency and select an available market to purchase. Next, they purchase the required quantities according to a periodic base-stock policy (R, T) with lost sales. Last, households consume their stock until the next review period.

The model calculates the nanostores' net profit, considering their fixed operation cost and variable supply costs against their sales revenues. Studies have found that small businesses usually have up to 60 days of cash in hand to function. Thus, after 90 days without sales, a small retailer would probably struggle to maintain their operations running (Bartik et al., 2020). Under this perspective, in this simulation we considered that nanostores with negative utilities from selling fruits and vegetables after 90 days of operations will decide to stop selling those products. In this case, their status in the simulation goes from "active" to "not active".

The following pseudocode illustrates the logic of the multi-agent-based model (Table 6).

Table 6. Simulation model pseudocode.

Inputs: $\Delta_{it} = 0$ for all nanostores

```
For t = 1 to T'
    ∀ i ∈ N
    //Nanostores update their stock
            I_it = I_i(t−1) + Σ_{h∈H} Q_hi(t−1)  // nanostore i updates its stock with the last day's demand (i.e. purchases from households)
            Δ_it = Δ_it + Σ_{h∈H} Q_hi(t−1)
            // The cumulative demand is updated
        If t mod 90 = = 0                  // every 90 days the profits are evaluated
        np_i = (p_i − c) Δ_it − f_i        // Calculate net profit during a 90 day period
        Δ_it = 0                           // Resets the cumulative demand of nanostore i
            If np_i ≤ 0
                Set status i = not active
            End If
        End If
    ∀ h ∈ H
    //Households review their stock and select market
        If t ∈ SD_h // if t is a shopping day of household h
            q'_ht = Σ_{t'=t−T_h}^{t'=t−1} δ_ht'   //calculation of the order quantity of household h on shopping day t based on the demand during the last review period
            s* = h.select(PS_ht, β)            // household h selects a seller. See below
            Q_hs*t = min(I_st, q'_ht)          // household h determines the quantity to buy depending on the seller's stock
            I_s*t = I_s*t − Q_hs*t             // selected seller updates its stock
```

Table 6. Continued...

Inputs: $\Delta_{it} = 0$ for all nanostores
Else $//t \notin SD_h$
$Q_{hs^*t} = 0$
End If
Generate a random demand δ_{ht} with a normal distribution $ND(\mu_h, \sigma_h)$ $I_{ht} = I_{h(t-1)} + Q_{hs^*t} - \delta_{ht}$
End
household member method: select(PS_{ht}, β)
$//PS_{ht}$ subset of valid sellers for housesold h on day t, and β is the set of weights calculated from the survey data.
// for all sellers s in PS_{ht}, calculate its probability of household h selecting seller s at day t (P_{hs}^t) with *Eq.* 1. The observed portion of the utility at day t, V_{hs}^t is given by:
$V_{hs}^t = \beta_{0s} + \beta_1 p_s + \beta_2 d_{hs} + \beta_3 sl_{st}$
//The observed portion of the utility is a linear combination of the seller's price, distance to the // household and the service level
Select a seller s^* according to the above probabilities Return s^*

First, a base scenario was run, with no disruptions. Then, four disruptive scenarios were run, exchanging values to frequency and duration of disruptions. All the scenarios were run considering the assumptions presented at Table 3.

5. Results and analysis

The results and analysis are split into two parts: a) investigating the impact of disruptive events in the food retail landscape and on nanostores' resilience, and b) analyzing the disruption effects on households' choice process. The agent-based simulation considers the proposed disruption scenarios in all the result analyses. This section provides a short list of practical takeaways based on our findings. Following, the variables of interest are presented, and the output of all scenarios are compared, leading to the analysis of critical factors and the characteristics of the most resilient stores.

5.1. Model calibration

This process consisted of establishing the values of β_l and of λ_k from the NLM of Equation 1, presented in section 2.3. These values were calculated using the classical maximum likelihood estimators based on the data collected from the household surveys. Considering that the $\beta_{distance}$ is different for each channel, the utility function used in this model was adjusted to $V_{hi} = \beta_{0r} + \beta_{1r} X_{1i} + \beta_{2r} X_{2i} \ldots + \beta_{lr} X_{li} \ldots + \beta_{LR} X_{Li}$, where X_{li} is the stated value of the l^{th} factor evaluated for the alternative i, and β_{lr} indicates the weight perceived for each factor per retail type *r*. The tool used for this calculation is Biogeme (Bierlaire, 2023). The analyzed attributes include the travel distance, the price, and the service level. The corresponding parameter values are shown in Table 7.

Table 7. Beta parameters values.

Retailer \ Parameter	β price	β distance	β Service Level
Supermarkets (all formats)		0	
Nanostores	-2.772	-0.177	0.1
Fruvers		-6.078	

Our regression results for the households were consistent with other studies (Ghosh-Dastidar et al., 2014) that set price and distance as the most critical factors affecting market choice.

5.2. Base scenario analysis

This subsection validates the average customer patterns and sellers' demands (including nanostores) under a baseline scenario (i.e., no disruption).

In this base scenario, the simulation resulted in nanostores capturing around 56.73% (±4.75) of the total market share, whereas supermarkets reached 42.18% (±4.08) and fruvers around 1.09% (±0.63). From the survey applied in the region, for the fresh food market, households' preferred retailer were nanostores with 56.96%, followed by supermarkets with 41.92% of the preference, and finally, fruvers with 1.12%, which validates the results obtained in the base scenario of the model.

About 13% of the orders were not fulfilled by nanostores due to stockouts, leading to a service level of 87%. The households' block order sizes of fruits and vegetables to nanostores were around 20% larger than to supermarkets and 6% smaller than to fruvers. Table 8 highlights the results of this scenario with the mean and standard deviation ($\mu(\pm\sigma)$) after 100 replicas.

Table 8. Base Scenario simulation results for nanostores.

Scenario	Average number of active nanostores	Demand Captured (%)	Service Level (%)
Base model	84 (±1.47)	56.73% (±4.75)	71.93 (±10.7)

Around 72% of all nanostores remained open through all the replicas. Most of them remained open around 84% of the runs. Figure 3 displays the regions where nanostores decided to continue retailing fruit and vegetables more frequently, marked in red. It is noticeable that the stores most frequently active are located in urban extensions, surrounding the downtown areas, where there is a larger quantity of competitors.

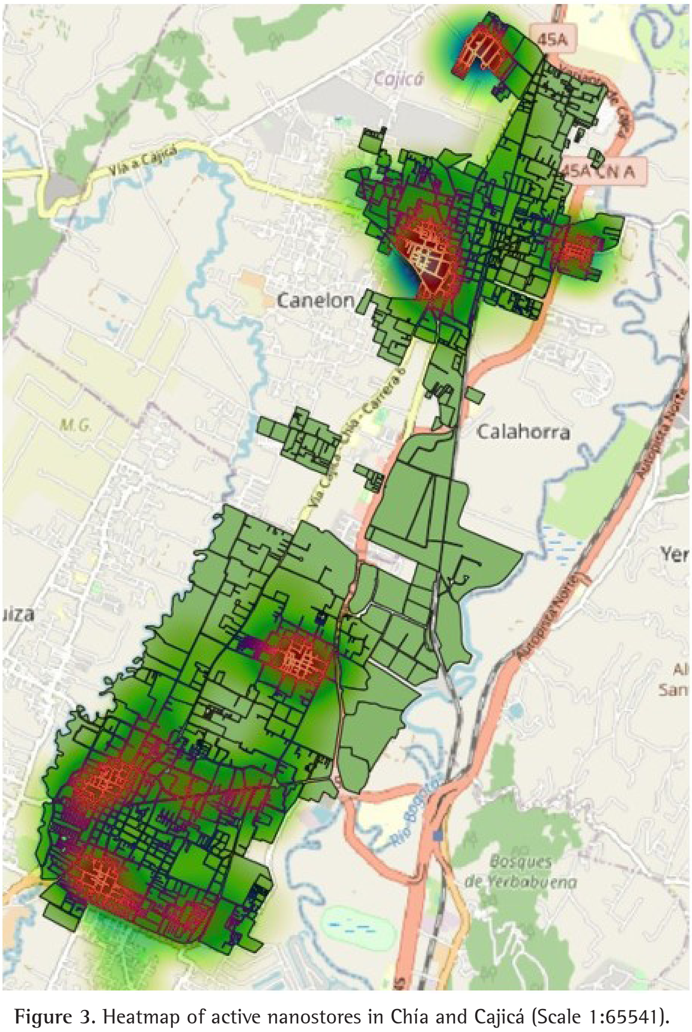

Figure 3. Heatmap of active nanostores in Chía and Cajicá (Scale 1:65541).

Conversely, according to simulation results, households spent around US$ 3.61 (±0.7) per kg of food. On average, households make 357 purchases during the simulation period of 1,000 days, which represents a trip every two to three days. However, the variation of retail visits among households varies considerably (SD = ± 256).

5.3. Scenarios analysis

We generated four scenarios, as presented in Table 3. The highlights of the effects generated among scenarios are described next.

5.3.1. Effects on the food landscape

Table 9 presents the effects on nanostores caused by each disruptive scenario. Clearly, the more disruptive the scenario, the higher the impact on market share and on the service levels.

Table 9. Effects on nanostores per scenario.

Scenario	MTTD (days)	MDOE (days)	Average active nanostores	Market share (%)	Service Level (%)
1	50	50	74 (±15)	51.95 (±13.35)	50.8 (±11.71)
2		100	58 (±29)	36.07 (±23.96)	22.40 (±13.31)
3	100	50	81 (±9)	55.54 (±7.58)	66.76 (±10.48)
4		100	71 (±22)	50.85 (±16.42)	52.13 (±11.78)

Across the different scenarios, it was evident that under disruptions, nanostores surrounding (but not inside) highly dense areas have a better probability of staying open, both in Chía and Cajicá (see Figure 4). However, stores located farther in developing and semi-rural regions are the first to be affected during the simulation. Figure 4 present the percentage of nanostores that remained open across all variations in scenarios for both study areas. The areas marked in red are the ones where nanostores remained "active" more frequently around all the replicas.

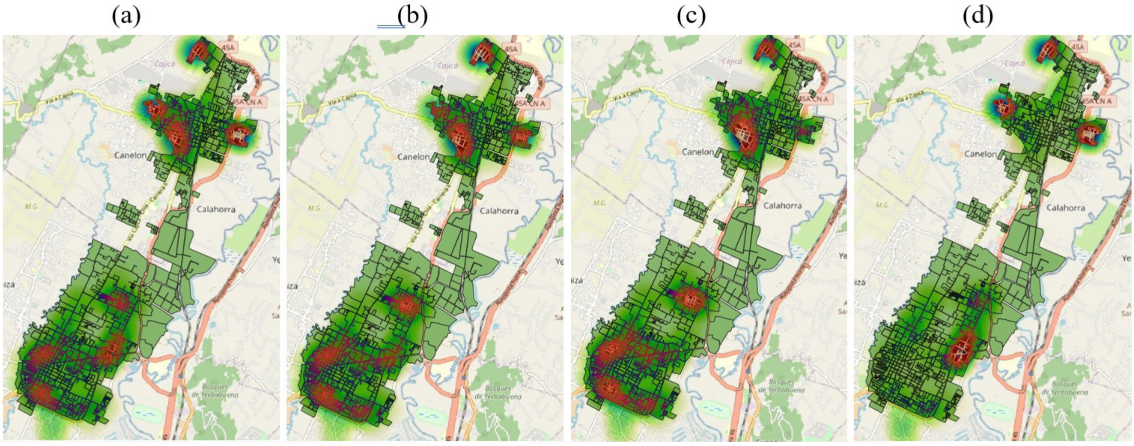

Figure 4. Active F&V retail nanostores across variations in Chía and Cajicá with (a) MTTD = 50 days MDOE = 50 days; (b) MTTD = 50 days MDOE = 100 days; (c) MTTD = 100 days MDOE = 50 days; (d) MTTD = 100 days MDOE = 100 days (Scale 1: 65541).

The average sales dropped significantly during the events, leading nanostores to reduce up to 33% of sales during the disruption period, as presented in Figure 5.

Accordingly, as duration of the disruption increased, supermarkets gained market share. The MTTD = 50 days scenario presented a quicker change of market share among retailer formats, due to its higher frequency of events occurring. Consequently, more nanostores stopped selling fruits and vegetables over time, with an average of

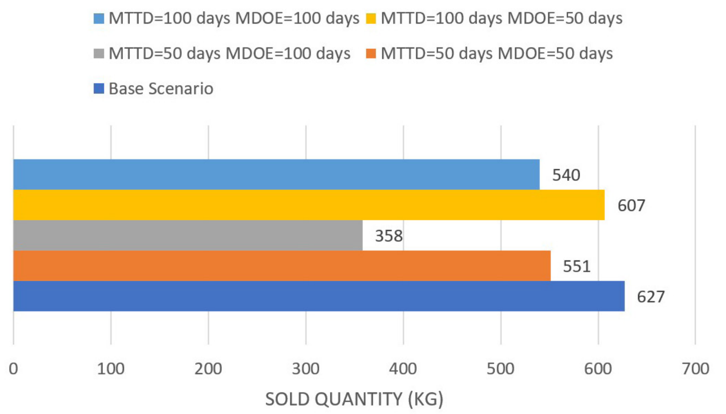

Figure 5. Average nanostores sales quantity variations across scenarios (in kg of food).

74 nanostores staying open after 1,000 days when MDOE = 50 days. When MDOE = 100 days, 58 nanostores remained open at the end of the run time. Likewise, frequent stockouts when MTTD = 50 days and MDOE = 100 days reduced nanostores' service level down to 22%.

With MTTD = 100 days and MDOE = 50 days, nanostores maintained a more significant market share through time, reaching over 55%. With MDOE = 100 days, the results presented an average of 71 nanostores remaining active; however, nanostores still manage to keep an average of over 50% of the market share by the end of the 1,000 simulation days. The service level varied from about 67% to 22% among all alternatives. In all scenarios, three nanostores never remain active retailing fruits and vegetables.

Supermarkets increased their participation up to about 60%, while fruvers only increased up to around 3% in the most disruptive scenario, as presented in Figure 6. The Figure shows the nanostores' market share behavior and how drastically frequent disruptions can affect their supply ability and, consequently, their market preference.

Finally, shopping sizes among retailers are very similar. Across scenarios, the shopping size is not significantly affected by disruptions to supermarkets and nanostores, representing around 1% increase. In fruvers, however, the shopping size was affected by up to 11%.

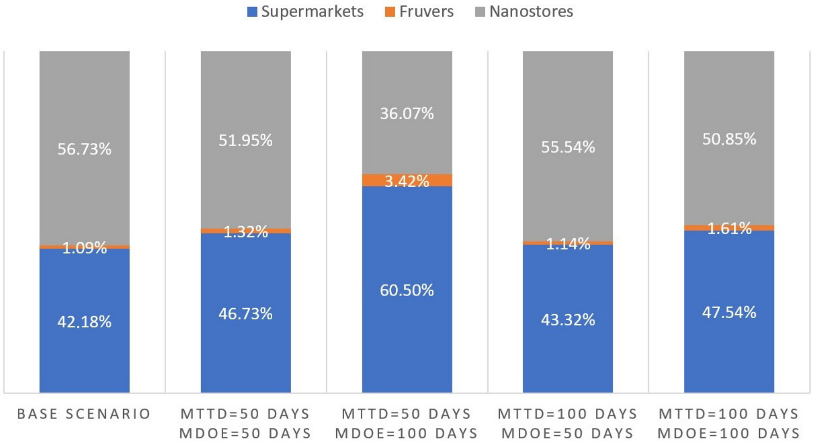

Figure 6. Retailers market share across scenarios.

5.3.2. Effects on households

The model adjusted the average demand per household block with each scenario variation. For example, we realized that with MTTD = 50 days, the demand decreases moderately, unlike the MTTD = 100 days scenario, which reduces the average demand per household in around 40% to 50% (See Figure 7).

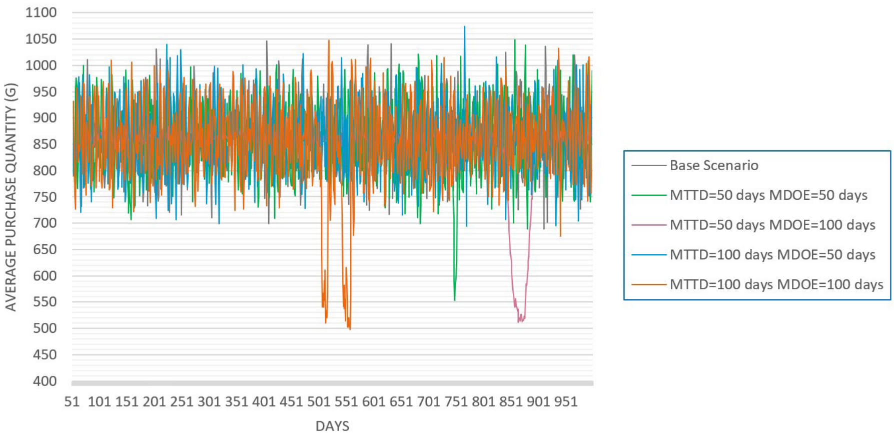

Figure 7. Average household purchase quantity variations across scenarios (in g of food per day).

Another relevant aspect found is that in very disruptive scenarios, the number of total visits to food retailers did not vary and is still very disperse. Additionally, while the average demand was reduced by less than 1% in all scenarios, the purchase quantities were affected during disruptions. Figure 7 presents the variations presented in purchase quantity through time. We can notice that, in the most disruptive scenario with one large disruption around day 850, the average purchase quantity for all households decreased up to 60%. In the scenario MTTD and MDOE = 100 days, two large disruptions took place very close to one another (approximately 40 days apart), generating a double effect in the purchase reduction. The scenario MTTD and MDOE = 50 days presented one disruption with lower effect and duration. It is interesting to notice that the disruption effect is perceived gradually in the market, and after the disruption, the market takes from 10 to 20 days to recover. Only in the case of the largest scenario disruption, the recovery period can be up to 30 days. However, in any case the household did not fulfill its demand. Overall, each household purchase quantity is never lower than 0.5 kg.

Changing retailers led households to slightly decrease the price paid per gram of food. On the baseline scenario, the average price per kg was around US$ 3.61 (±0.17), which slightly reduced to US$ 3.47 in the most disruptive scenarios (See Table 10). The most affected scenarios were those with higher MDOE values.

Table 10. Effects on households per scenario.

Scenario	MDOE (days)	Cost per food (US$/Kg)
Scenario 1	50	3.61 (±0.8)
	100	3.47 (±0.97)
Scenario 2	50	3.61 (±0.71)
	100	3.51 (±0.92)

6. Discussion and conclusions

The results of this study provide insights on how nanostores operations could be affected by disruptive events. Among the results, we noticed that the first shift in the food landscape is that consumers will mainly migrate to supermarkets (up to 18%) when a disruption occurs according to our model. Thus, if a nanostore is not available in their surroundings, households would be willing to travel larger distances to visit supermarkets rather than fruvers. This may be explained by the variety in assortment of fruvers, which is usually more limited than its competitors.

The changes in the food retail landscape were faster and more severe with lower values of MTTD and higher values of MDOE, as expected. When MDOE = 100 days, all variations of MTTD presented a similar market behavior, with larger effects on the households purchase and in nanostores sales.

Additionally, when MTTD = 100 days, even after a large disruption, nanostores maintained a significant market share for nanostores in all cases, and a substantial service level (at least 52%). These results show

how sensitive the market might be to more abrupt and continuous disruptions, establishing that even longer periods of disruptions will not affect radically this channel if the frequency of disruptions is lower. This can be explained because with closer events with different durations, their effects may overlap and increase the disruption levels in specific periods. Another interesting factor is that the household purchase frequency was only slightly affected by disruptions, accompanied by changes in demand. Further, the average price paid per kg of fresh food decreased across scenarios, which can be explained because the households migrated first to supermarkets, that are usually cheaper than the nanostores.

The model also showed that factors such as price and distance are relevant if retailers are available in a region. When the number of retailers is reduced, and the remaining retailers have supply limitations (such as fruvers), consumers will migrate to larger supermarkets, even if it represents an increase in their commute behavior and in their purchase habits. This represents a key factor to be explored by traditional retailers, considering that their presence in underserved areas farther to city centers drives the household purchase decision.

However, for many nanostores, it is expensive to supply their establishments because of their low negotiation power with major suppliers. Thus, they are more vulnerable to stockouts and to a reduction of utilities when disruptions strike. In consequence, their vulnerability and potential closure affects their surroundings significantly, forcing households to select farther and more expensive channels. Hence, these small, family-owned retailers could supplement the food offered in several city areas by complementing their assortment and increasing their economies of scale, generating more stability for larger periods. To improve their supply capacity and reduce the involved risk of assortment can be determinant for nanostores that have shown to be more resilient under disruptions, such as the ones boarding downtown areas.

7. Managerial implications

We believe that this research contributes to the state of the art in the discipline by building knowledge about how nanostores resilience affects food landscapes in emerging markets. With our hybrid approach, we could investigate the impact of disruptive events on the retail food landscape, the changes in household demand patterns and the choice of distribution channels (i.e., sellers), and the logistics trade-offs carried out by the changes. Results show that the presence of nanostores may represent better food access for underserved households, due to their preference of this channel in regions where other channels are not present. However, given their limited capacity, the proposal would hardly deal with an entire region's current (and future) food demand. Despite these limitations, nanostores are a force to reckon with to address significant issues in fragmented retail landscapes. Further research is needed to predict their survival and the effects they might have to combat food malnutrition worldwide.

A final thought is that implementing a strategic plan to improve food access for vulnerable communities requires (i) a combination of diverse retail formats and (ii) better supply chain management practices.

Acknowledgements

We thank RAP-E for their leadership in the data collection process. Further, we thank the involved academic institutions for supporting this research: Universidad de la Sabana, Universidad Privada Boliviana, and Massachusetts Institute of Technology. Finally, we thank ICETEX for financially aiding this project.

References

Awasthi, A., Chauhan, S. S., & Goyal, S. K. (2011). A multi-criteria decision making approach for location planning for urban distribution centers under uncertainty. *Mathematical and Computer Modelling*, *53*(1-2), 98-109. http://doi.org/10.1016/j.mcm.2010.07.023.

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). *How are small business adjusting to COVID-19? Early evidence from a survey.* Cambridge: National Bureau of Economic Research. http://doi.org/10.3386/w26989.

Bierlaire, M. (2023). *A short introduction to Biogeme* (Technical Report, No. TRANSP-OR 230620). Lausanne: EPFL.

Boulaksil, Y., & Belkora, M. J. (2017). Distribution strategies toward nanostores in emerging markets: the Valencia case. *Interfaces*, *47*(6), 505-517. http://doi.org/10.1287/inte.2017.0914.

Boulaksil, Y., Fransoo, J. C., Blanco, E. E., & Koubida, S. (2019). Understanding the fragmented demand for transportation: small traditional retailers in emerging markets. *Transportation Research Part A, Policy and Practice*, *130*, 65-81. http://doi.org/10.1016/j.tra.2019.09.003.

Brown, J. R., & Guiffrida, A. L. (2017). Stochastic modeling of the last mile problem for delivery fleet planning last mile algorithm comparison view project stochastic modeling of the last mile problem view project. *Journal of the Transportation Research Forum*, *56*(2), 93-108.

Brown, J. R., Bushuev, M. A., & Guiffrida, A. L. (2021). “Distance metrics matter: analysing optimisation algorithms for the last mile problem. *Inderscience Publishers*, *38*(2), 151-174. http://doi.org/10.1504/IJLSM.2021.113233.

Cajamarca, I. (2022, Junio 11). *‘Tiendas para la Gente’ fortalecerá a 5.700 tiendas de barrio afectadas por el COVID-19*. La República.

Calisti, R., Proietti, P., & Marchini, A. (2019). Promoting sustainable food consumption: an agent-based model about outcomes of small shop openings. *Journal of Artificial Societies and Social Simulation*, *22*(1), 2. http://doi.org/10.18564/jasss.3901.

Colombia, Departamento Administrativo Nacional de Estadística – DANE. (2022). *Geoportal DANE*. Bogotá D.C. Retrieved in 2023, July 5, from https://geoportal.dane.gov.co/servicios/descarga-y-metadatos/datos-geoestadisticos/?cod=111

Constanza Gómez, G. (2005, Noviembre 25). *Los fruver, un modelo de los comerciantes que crece para atender a clientes exigentes*. El Tiempo.

Cummins, S., Smith, D. M., Aitken, Z., Dawson, J., Marshall, D., Sparks, L., & Anderson, A. S. (2010). Neighbourhood deprivation and the price and availability of fruit and vegetables in Scotland. *Journal of Human Nutrition and Dietetics*, *23*(5), 494-501. http://doi.org/10.1111/j.1365-277X.2010.01071.x. PMid:20831708.

Escamilla, R., Fransoo, J. C., & Tang, C. S. (2021). improving agility, adaptability, alignment, accessibility, and affordability in nanostore supply chains. *Production and Operations Management*, *30*(3), 676-688. http://doi.org/10.1111/poms.13309.

Fenalco. (2022). *La tienda de barrio sigue siendo la joya de la corona para los productos de consumo masivo*. Retrieved in 2024, May 28, from https://www.fenalco.com.co/blog/gremial-4/la-tienda-de-barrio-sigue-siendo-la-joya-de-la-corona-para-los-productos-de-consumo-masivo-456

Food and Agriculture Organization – FAO, International Fund for Agricultural Development – IFAD, United Nations Children’s Fund – UNICEF, World Food Programme – WFP, World Health Organization – WHO. (2022). *The state of food security and nutrition in the world 2022 - repurposing food and agricultural policies to make healthy diets more affordable*. Rome: FAO.

Fransoo, J. C. (2021). *Nanostore supply chains leverage the Triple A: agility, adaptability and alignment*. LinkedIn. Retrieved in 2023, August 1, from https://www.linkedin.com/pulse/nanostore-supply-chains-leverage-triple-agility-jan-fransoo/

Fransoo, J. C., Blanco, E., & Mejía-Argueta, C. (2017). *Reaching 50 million nanostores: retail distribution in emerging megacities*. Scotts Valley: CreateSpace.

Freitas, E., & Domingues, N. (2013). The economy of distribution centers: the case of large retail networks in Brazil. *African Journal of Business Management*, *7*(16), 1541-1552. http://doi.org/10.5897/AJBM2013.1579.

Ge, J., Honhon, D., Fransoo, J. C., & Zhao, L. (2021). Supplying to mom and pop: traditional retail channel selection in megacities. *Manufacturing & Service Operations Management*, *23*(1), 19-35. http://doi.org/10.1287/msom.2019.0806.

Ghosh-Dastidar, B., Cohen, D., Hunter, G., Zenk, S. N., Huang, C., Beckman, R., & Dubowitz, T. (2014). Distance to store, food prices, and obesity in urban food deserts. *American Journal of Preventive Medicine*, *47*(5), 587-595. http://doi.org/10.1016/j.amepre.2014.07.005. PMid:25217097.

Gutiérrez-Rubiano, D. F., Hincapié-Montes, J. A., & León-Villalba, A. F. (2019). Collaborative distribution: strategies to generate efficiencies in urban distribution: results of two pilot tests in the city of Bogotá. *Dyna*, *86*(210), 42-51. http://doi.org/10.15446/dyna.v86n210.78931.

Kin, B. (2020). Less fragmentation and more sustainability: how to supply nanostores in urban areas more efficiently? *Transportation Research Procedia*, *46*, 117-124. http://doi.org/10.1016/j.trpro.2020.03.171.

Kin, B., Ambra, T., Verlinde, S., & Macharis, C. (2018). Tackling fragmented last mile deliveries to nanostores by utilizing spare transportation capacity: a simulation study. *Sustainability*, *10*(3), 653. http://doi.org/10.3390/su10030653.

Larrea-Gallegos, G., Benetto, E., Marvuglia, A., & Navarrete Gutiérrez, T. (2022). Sustainability, resilience and complexity in supply networks: a literature review and a proposal for an integrated agent-based approach. *Sustainable Production and Consumption*, *30*, 946-961. http://doi.org/10.1016/j.spc.2022.01.009.

Levi, R., Paulson, E., & Perakis, G. (2020). *Fresh fruit and vegetable consumption: the impact of access and value* (MIT Sloan Research Paper, No. 5389-18). Rochester: SSRN. http://doi.org/10.2139/ssrn.3691925.

Macal, C. M., & North, M. J. (2007). Agent-based modeling and simulation: desktop ABMS. In *Proceedings - Winter Simulation Conference* (pp. 95-106). New York: IEEE. http://doi.org/10.1109/WSC.2007.4419592.

Mejía, G., & García-Díaz, C. (2018). Market-level effects of firm-level adaptation and intermediation in networked markets of fresh foods: a case study in Colombia. *Agricultural Systems*, *160*, 132-142. http://doi.org/10.1016/j.agsy.2017.06.003.

Mejia Argueta, C., Udenio, M., Mutlu, N. R., & Fransoo, J. C. (2019a). *Are nanostores there to stay in emerging markets?* (Working Paper). Cambridge: MIT Center for Transportation and Logistics.

Mejía-Argueta, C., Benitez-Perez, V., Salinas-Benitez, S., Brives, O., Fransoo, J. C., Salinas-Navarro, D., & Rangel, G. (2019b, August 15). *Nanostores, a force to reckon with to fight malnutrition*. LinkedIn. Retrieved in 2022, September 17, from https://www.linkedin.com/pulse/nanostores-force-reckon-fight-malnutrition-escf-professors/

Mora-Quiñones, C. A., Cárdenas-Barrón, L. E., Velázquez-Martínez, J. C., & Gámez-Pérez, K. M. (2021). The coexistence of nanostores within the retail landscape: a spatial statistical study for Mexico City. *Sustainability*, *13*(19), 10615. http://doi.org/10.3390/su131910615.

Moyano, M., Castillo, J., Chong, M., & Mejía, C. (2022). Comparison of nanostore supply chain strategies in urban areas: the case of Ica, Peru. *Springer Proceedings in Mathematics and Statistics*, *391*, 513-531. http://doi.org/10.1007/978-3-031-06862-1_39.

Nogueira, L. R., Fontanelli, M., Aguiar, B. S., Failla, M. A., Florindo, A. A., Barrozo, L. V., Goldbaum, M., Cesar, C., Alves, M., & Fisberg, R. (2018). Access to street markets and consumption of fruits and vegetables by adolescents living in São Paulo, Brazil. *International Journal of Environmental Research and Public Health*, *15*(3), 517. http://doi.org/10.3390/ijerph15030517. PMid:29538324.

Paswan, A., Santarriaga Pineda, M. D., & Soto Ramirez, F. C. (2010). Small versus large retail stores in an emerging market—Mexico. *Journal of Business Research*, *63*(7), 667-672. http://doi.org/10.1016/j.jbusres.2009.02.020.

Rios Monroy, J. (2020). *Cultivos en Colombia durante la pandemia por coronavirus*. El Tiempo.

Ritter, F. E., Schoelles, M. J., Quigley, K. S., & Klein, L. C. (2011). Determining the Number of Simulation Runs: Treating Simulations as Theories by Not Sampling Their Behavior. In L. Rothrock, S. Narayanan (Eds.), Human-in-the-Loop Simulations (pp. 97-116). London: Springer. http://doi.org/10.1007/978-0-85729-883-6_5.

Sabana Centro Cómovamos. (2017). *Municipios.* Chía, Colombia. Retrieved in 2023, April 5, from https://sabanacentrocomovamos.org/municipios/

Sabana Centro Cómovamos. (2021). *Informe de calidad de vida 2020* (Vol. *6*). Chía, Colombia.

Salinas-Navarro, D. E., Pacheco-Velazquez, E., Silva-Ovando, A. C., Mejia-Argueta, C., & Chong, M. (2024). Educational innovation in supply chain management and logistics for active learning in Latin America. *Journal of International Education in Business*, *17*(1), 148-169. http://doi.org/10.1108/JIEB-07-2023-0050.

Shaaban, M., Voglhuber-Slavinsky, A., Dönitz, E., Macpherson, J., Paul, C., Mouratiadou, I., Helming, K., & Piorr, A. (2023). Understanding the future and evolution of agri-food systems: a combination of qualitative scenarios with agent-based modelling. *Futures*, *149*, 103141. http://doi.org/10.1016/j.futures.2023.103141.

Shoukat, A., & Moghadas, S. (2020). Agent-based modelling: an overview with application to disease dynamics. *ArXiv*, arXiv:2007.04192.

Silva-Ovando, A. C., Granados-Rivera, D., Mejía, G., Mejía-Argueta, C., & Jarrín, J. (2021). Spatial analysis of fresh food retailers in Sabana Centro, Colombia. In L. Rabelo, E. Gutierrez-Franco, A. Sarmiento & C. Mejía-Argueta (Eds.), Engineering analytics (pp. 235-253). Boca Raton: CRC Press. http://doi.org/10.1201/9781003137993-15.

Sopha, B. M., Sri Asih, A. M., Pradana, F. D., Gunawan, H. E., & Karuniawati, Y. (2016). Urban distribution center location: combination of spatial analysis and multi-objective mixed-integer linear programming. *International Journal of Engineering Business Management*, *8*, 1-10. http://doi.org/10.1177/1847979016678371.

Sturley, C., Newing, A., & Heppenstall, A. (2018). Evaluating the potential of agent-based modelling to capture consumer grocery retail store choice behaviours. *International Review of Retail, Distribution and Consumer Research*, *28*(1), 27-46. http://doi.org/10.1080/09593969.2017.1397046.

Swinburn, B., Sacks, G., Vandevijvere, S., Kumanyika, S., Lobstein, T., Neal, B., Barquera, S., Friel, S., Kelly, B., Kumanyika, S., L'Abbé, M., Lee, A., Lobstein, T., Ma, J., MacMullan, J., Mohan, S., Monteiro, C., Neal, B., Rayner, M., Sanders, D., & Walker, C. (2013). What are 'food environments'? *EPHA*, *14*(Suppl 1), 24-37. PMid:24074208.

Torrens, P. M. (2023). Agent models of customer journeys on retail high streets. *Journal of Economic Interaction and Coordination*, *18*(1), 87-128. http://doi.org/10.1007/s11403-022-00350-z.

Train, K. E. (2009). *Discrete choice methods with simulation* (2nd ed.). Berkeley: Cambridge University Press.

United Nations. (2020). *Cómo evitar que la crisis del COVID-19 se transforme en una crisis alimentaria: acciones urgentes contra el hambre en América Latina y el Caribe*. Santiago de Chile: CEPAL.

van Voorn, G., Hengeveld, G., & Verhagen, J. (2020). An agent based model representation to assess resilience and efficiency of food supply chains. *PLoS One*, *15*(11), e0242323. http://doi.org/10.1371/journal.pone.0242323. PMid:33211734.

Widener, M. J., Metcalf, S. S., & Bar-Yam, Y. (2012). Developing a mobile produce distribution system for low-income urban residents in food deserts. *Journal of Urban Health*, *89*(5), 733-745. http://doi.org/10.1007/s11524-012-9677-7. PMid:22648452.

Zhang, J., & Robinson, D. T. (2022). Investigating path dependence and spatial characteristics for retail success using location allocation and agent-based approaches. *Computers, Environment and Urban Systems*, *94*, 101798. http://doi.org/10.1016/j.compenvurbsys.2022.101798.

Zissis, D., Aktas, E., & Bourlakis, M. (2018). Collaboration in urban distribution of online grocery orders. *International Journal of Logistics Management*, *29*(4), 1196-1214. http://doi.org/10.1108/IJLM-11-2017-0303.