Assessing the Impact of Progressive Licencing Fee Policies on Tobacco Retail Dynamics: An Agent-Based Modeling Approach

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Abstract

Retailer licensing fees are often regarded as a powerful instrument for reducing tobacco availability. However, their implementation poses challenges due to the financial impacts they may have on retailers operating in diverse environmental conditions. We developed an agent-based model to examine the financial impact of implementing a progressive license fee with three fee structures (universal, volumetric, and urban/rural) on retailers with different socioeconomic conditions and the resulting changes in smoking consumption patterns. The results showed that each fee structure has a different spatial impact on retailer reduction and gross profit distribution. On the other hand, consumption patterns will not be significantly affected unless an aggressive annual fee increment is applied. We find that progressive license fee schemes can serve as a strategic policy instrument that can be flexibly adjusted to reduce the availability of tobacco retailers in accordance with predetermined objectives. However, their implementation will heavily depend on the fee structure used, the size of the initial base fee, the level of annual increment, the geographical location of the retailers, and the potential price competition among them.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Geri Noorzaman*)

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All praise is for Allah, the Lord of the universe. Without His divine guidance, strength, and boundless mercy, this dissertation would not have been possible. ”Which of the favors of your Lord would you deny?”

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As George Box wisely said, ”All models are wrong, but some are useful.” I hope the model developed through this project will serve as a useful tool for those who come after. Remember, the best of people are those who are most beneficial to people.

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Chapter 1

Introduction

1.1 Motivation

Tobacco retailer licencing stands as a pivotal tool within tobacco control policies. This scheme is regarded as one of the most effective regulatory approaches in diminishing tobacco use [1, 2, 3]. In the licencing system, retailers wishing to sell tobacco legally must acquire a special licence from the authority and periodically renew this licence [4]. Implementing fees into this scheme can decrease tobacco retailer density as retailers opt to cease tobacco sales due to increased costs that affect profits [5] or to avoid the hassle of managing and paying this fee [6]. Previous retail environment study by [7] found that this reduction by retailers can further discourage people from consuming tobacco and, in turn, reduce smoking prevalence.

However, introducing such fees would be an uphill battle. Its application may result in varying impacts on retailers with various characteristics and environmental conditions. Licencing fees, with their varied structures, can significantly impact retailers and local communities [5]. Retailers are at odds with these kinds of policies since these fees could negatively impact their profits [8]. Moreover, retailers in rural and deprived areas also play a vital role in local economic growth and social engagement [9]. As a result, communities also have to carry the weight, as the implementation of licence fees can adversely affect their local economic condition.

Despite the recognised importance, only a limited number of studies currently assess the effects of licencing fees on retailers with differing sociodemographic conditions [10]. In recent research, Valiente et al. [5] analysed the impact of applying a licencing scheme with varied fee structures on the retailers' gross profits in Scotland. These retailers are classified into five categories based on neighborhood deprivation and urbanicity.

While they were able to demonstrate the effects of licence fees on various retailers, they utilised a limited mathematical model approach that did not consider the dynamic nature of the retail tobacco environment. The model struggled to elucidate the impact on retailers in scenarios with increased licencing fees over a certain period. Additionally, retailers would likely take proactive measures to mitigate potential profit losses. They may pass some or all of the increased cost to customers [11], leading to an increase in retail tobacco price. Nevertheless, the model falls short in simulating and explaining the impact of these scenarios.

To address these problems, we propose the use of Agent-Based Modelling (ABM). This approach helps us to unveil the impacts of establishing higher fee schemes for retailers across diverse socioeconomic areas. [12] defines ABM as a computational modeling approach used in simulating behaviors and interactions of heterogeneous agents. It is a potent tool now commonly used for public health research [13] and has often been considered a crucial instrument for assessing tobacco control policies [14]. In our research, ABM grants autonomy to create an artificial environment to simulate smokers, retailers, policy environment, and their interactions over time. The resulting complex behaviors and outcomes can then be analysed, offering insights into how these phenomena develop [15].

1.2 Problem Statement

Most studies on licencing fees rely on equation-based modeling. Such an approach struggles to examine the dynamics of system behaviors that can not be all formalised mathematically [15]. This background calls for the development of a new agent-based model that can capture the heterogeneous actions of the agents and provide insights for future decision-making. In building such a model, the following research questions emerge:

- How does the increase of licencing fees over time influence the availability of different tobacco retailers based on their sociodemographic characteristics (e.g., urban vs. rural, high-deprived vs. low-deprived)?
- What are the potential disparities in the impact of the increase of different licencing fee structures on retailers based on their location and size?
- How might changes in the retail environment, induced by varying licencing fee structures, affect consumption patterns across communities?

Addressing these research questions, the model developed aims to offer key insights into how licence fees can impact retailers with diverse sociodemographic conditions. Furthermore, this research project is conducted in collaboration with the Scottish Government. By providing a robust model that captures the dynamic behaviors and complexity of agents' interactions, this study offers regulators a foundation for future policymaking.

The research hypothesis suggests that escalating different structures of licencing fees will differentially impact retailers based on their sociodemographic characteristics. This hypothesis is underpinned by prior research indicating that variable fee structures can influence different retail behaviors and market dynamics [5, 16, 17]. In addition, it is important to note that this study will not further assess the wider impacts on public health and the economy. The crux of the analysis will be on the immediate financial implications on retailers and subsequent impact on consumption patterns and smoking prevalence.

1.3 Structure

This thesis is organised as follows: Chapter 2 provides an overview of licencing fee policies, discusses their implementation across jurisdictions, and explores the potential of Agent-Based Models (ABMs) for assessing these fees, highlighting this project's contributions. Chapter 3 details the design of the agents within the model, including their state variables, actions, interactions, and underlying assumptions. Chapter 4 validates the model against observed data to ensure its robustness. Chapter 5 presents the results and analysis by examining agent behavior and connects findings to the research questions. Finally, Chapter 6 summarises the findings, discusses policy implications, and suggests areas for future research.

Chapter 2

Background and Related Work

2.1 Tobacco Licencing Fees

2.1.1 Licencing Fee Scheme: An ”Endgame Intervention”

Tobacco retailer licencing is often considered the heart and soul of tobacco control policies. It is one of a potent weapons in the arsenal of tobacco control strategies endorsed by the World Health Organization (WHO) [18] and is considered one of the ”endgame interventions” [19] aimed at achieving swift and dramatic reductions in smoking prevalence [20].

Like a domino effect, the implementation of licencing fees can provide multiplied benefits. Firstly, such fees can boost retailer compliance [21], reduce illicit sales [22], and strengthen the enforcement of existing tobacco control policies among retailers, including age-of-sale laws [22, 2], bans on the display or promotion of tobacco products, and regulations on taxation and minimum pricing [2]. Additionally, attaching fees can also reduce the density of tobacco retailers [23]. Some may opt to discontinue tobacco sales due to the increased costs affecting their profits [24, 25], or some of them feel objected to managing the administrative tasks and paying an annual licencing fee [6]. Studies have found that reducing the availability of tobacco retailers has proven its worth in decreasing tobacco consumption [26], leading to a decline in smoking prevalence [7, 27] and more favorable smoking outcomes for both youths [28, 29] and adults [30].

Fifty-three countries[1] have licencing systems with various schemes and fee structures. These fees have taken root in several European countries, including Finland, Hungary, and Spain. Finland has utilised a licence fee since 2009, requiring retailers to pay a fee ranging from €100 to €180 (depending on the municipality) plus an annual

[1] In 2024, based on a study by [5]

renewal fee of €500 [2, 31]. Hungary has implemented one of the strictest licencing schemes [2], mandating that retailers apply, pay, and obtain a licence through an auction system [32]. In Spain, the licencing scheme is monopolised by the government, with retailers required to pay a fee based on the population size of their settlement and the volume of their sales[2] [24, 5]. Similar fee patterns are also observed in the United States [33] and Australia [34]. In California, since 2016, retailers must pay an annual fee of $265 [35], while in Western Australia, tobacco sellers are required to pay application and annual fees ranging from $270 to $640, depending on the size of the retailer [34].

Valiente et al. [5] classified the structure of licencing fees into three main categories: universal, volumetric, and urban/rural. The universal fees involve single flat fees imposed on all retailers regardless of their features or location. Meanwhile, volumetric fees require retailers to pay fees in proportion to a specific metric, such as sales volume or revenue. Lastly, the urban/rural scheme applies differential flat fees for retailers based on urban and rural locations. These three structures represent typical schemes implemented globally and will be incorporated as the cornerstone of our design model.

2.1.2 The Challenges

On the other hand, Scotland has not yet implemented a licencing system. Since 2010, retailers are only required to register with the Scottish Tobacco Retailer Register [5], which the Scottish Government maintains, without fees. Implementing a licencing scheme has indeed been considered, but there are various challenges from local authorities and retailers [2, 8]. However, with the renewed commitment toward a smoke-free generation by 2034, the Scottish Government is now actively considering revising the current tobacco retailer registration system by introducing licencing fees. With the finish line set at reducing adult smoking rates to less than 5% by 2034 [36, 37], reevaluating this framework to include a fee scheme potentially represents a significant policy shift.

Like two sides of the same coin, every policy has its strengths and weaknesses, including licencing fee policies. Opinions are divided regarding the implementation of these policies. The tobacco industry has strongly opposed the licencing system, spreading misinformation and encouraging retailers to speak out against the proposed policy [2]. Retailers' potential loss of profit is the standard line of defence used to counter such policies. Moreover, similar to other tobacco control interventions, implementing a licencing fee scheme can create disparities among retailers from different

[2] €240.40 for settlements with over 100,000 residents, €180.30 for settlements with 10,000–100,000, or €120.20 for settlements with fewer than 10,000

socioeconomic backgrounds [38, 39, 40]. Given the rich tapestry of Scottish retail environments, small retailers located in rural and deprived communities must receive significant attention. Implementing licencing fees should uphold their central role as the driving force of economic and social growth in these areas.

2.1.3 Recent Research

As one of the endgame interventions in tobacco control policies, there is a substantial body of research focused on licencing systems. Numerous publications cover these schemes extensively, including their potential, practice, and effectiveness in various jurisdictions. The formulation and execution of such public health policies come with a long-standing tradition of being informed by evidence from experiments, natural observations, and statistical models [41, 5, 33, 17, 42].

[41] investigated the impact of a significant increase in tobacco retailer licencing fees in South Australia. The study utilised an interrupted time-series analysis to assess the effects of raising the annual tobacco licence fee from $12.90 to $200, a more than fifteen-fold increase. With a dramatic decrease to more than 23.7% tobacco licences from 2007 to 2009, the authors concluded that licencing fees could serve as a game changer to curb the availability of tobacco products, with the significant impact in areas with lower consumer demand. While the study offers valuable insights on reducing tobacco retailers due to increased licencing fees, it falls short in presenting a holistic view of the financial state of retailers based on different socioeconomic conditions.

Similarly, [35] analysed the impact of increasing licencing fees in California and described the impacts on retailer density changes by neighborhood income and ethnicity. Using the same interrupted time-series analysis, the researchers found that the retailer density decreased by 3.5% immediately, with the most significant reductions observed in low-income and majority-black zip codes. Complementing the study by [41], this study highlights the efficacy of increased licencing fee policies and emphasises the pro-equity effects of such policies in economically disadvantaged and minority communities. However, similar to the previous study, the authors did not delve into the financial consequences for retailers. Though they detailed the reductions by socioeconomic and racial/ethnic categories, the retailers' financial state remained in the 'black box'.

The most recent study by Valiente et al. [5] is one of the few research efforts that examine the immediate financial impacts of licencing fees on retailers. Using massive transaction data from 179 convenience stores in Scotland, this study gave a complete view into the monetary impacts of different tobacco licencing fee structures on small retailers. The authors used a combination of gross profit calculations and simple scenario modeling to compare three different fee structures. They concluded that universal fees disproportionately affect retailers with lower sales volume in rural and less deprived areas; in contrast, volumetric fees more equitably distribute the financial burden according to sales volume, while rural/urban fees favor more retailers in the high-deprivation areas. Unlike previous studies by [41, 17], the authors comprehensively analysed how different fee structures affect retailer profits across various socioeconomic conditions. They offered insights about the importance of considering spatial and economic disparities when designing tobacco licencing policies.

Most studies on licencing fees rely on statistical analysis and equation-based models to understand these fees' impact. However, as mentioned earlier, this approach often fails to capture the dynamic nature of the retail tobacco environment. Retailers are not born yesterday and will likely respond to mitigate potential profit losses. For instance, they may implement price-discriminating strategies to pass on the cost increase to customers [11, 43]. To complicate matters, they can also maintain competitiveness by monitoring their neighbors' prices, making their behavior more complex and dynamic. This research project tries to fill that gap by employing ABMs to better integrate those adaptive behaviors and uncover more insights to better support policy making processes.

2.2 ABMs for Tobacco Policy Modeling

2.2.1 Why Use ABMs?

Existing models in prior research typically do not account for interactions among individuals within a population. Considering that smoking is predominantly associated with social and individual behaviors, it is essential to model these processes to understand the potential impact of a given policy [14]. One advantage of ABMs is their capacity to consider agent variations and how agents might influence one another. This capability enables evaluating the collective impacts of the multiple processes that constitute tobacco use behavior [14]. Given the significant social aspect of tobacco use and the diverse nature of these social interactions, ABMs can be a vital instrument for evaluating the impact of tobacco control measures, including licencing fee systems.

One of the main challenges in implementing licencing fee schemes and other tobacco policies is the inherently dynamic nature of the tobacco environment. Retailers and customers can alter their behavior in response to implementing these policies. Moreover, a vital concern of this research project is how to design effective licencing fee policies without exacerbating disparities between communities. Failure to anticipate individuals' behavioral responses and identify potential negative impacts on diverse environments will result in ineffective policy implementation. However, anticipating these responses is challenging due to limited knowledge of human behavior and the complex interactions between individuals and their social environment [14].

ABMs possess the necessary flexibility to serve as effective platforms for developing new policies [44] and are particularly adept at addressing the challenges above. They can capture intricate spatial structures and dynamics, essential for considering inherently spatial, retail-oriented policies [45]. ABMs excel at modeling adaptive behavior over time, such as the responses of consumers and retailers to changes in the retail regulatory environment. They also allow for comparisons of many real-world policy combinations that are challenging to achieve through real-world experiments [45].

2.2.2 Recent Research

The last decade has witnessed an increasing uptake of ABMs to complement the traditional tools[3] in policy design [46]. Despite the extensive literature on tobacco control, there is a noticeable gap in studies utilising ABMs to assess the impact of licencing fee policies on retailers based on sociodemographic factors.

Levy et al. [47] evaluated the effectiveness of tobacco control policies in Korea using the SimSmoke model. They built a simulation tool that assesses the impact of various policies on smoking initiation, cessation, and mortality. However, despite successfully simulating the impact of the implemented policies, the model failed to capture the adaptive behaviors of retailers and consumers over time. SimSmoke effectively showcased policy impacts in static scenarios but did not address how retailers might adjust their strategies in response to policy changes. A similar simulation may also be found in [48], which expanded this approach in Ireland by utilising a broader scope of policy coverage. Both studies illustrated ABM's effectiveness in evaluating policy impacts on smoking prevalence. Yet, they did not explore the effects of licencing fees or delve into the impacts on retailers.

Other research delves into the effects of retail-density-based policies through spatial contextual models. [49, 46] developed an agent-based model named "Tobacco Town" to investigate point-of-sale policies within a simulated environment that includes homes, schools, workplaces, and retailers. This model assessed the dynamic nature of adult

[3] Traditional tools refer to experiments, natural observations, and statistical models [46].

smokers navigating daily routines, including their commutes to purchase cigarettes. The focal point of the study was to analyse the implications of retailer reduction through random selection and proximity restrictions. [50] expanded this model to be used in Minnesota to examine the consequences of menthol cigarette sales bans and retailer density reductions across various community types. Both studies highlight ABM's capability to elucidate the effects of tobacco control policies on retailer dynamics without explicitly simulating licencing fees. Instead of integrating licencing fees, these models simulate direct retailer reductions. Notably, the retailers in these models are depicted as relatively passive, unable to actively respond to the simulated policies.

Another research area worth mentioning is the exploration of social and socioeconomic influences on smoking behaviors using ABMs. [51] analysed how socioeconomic disparities within and between gender groups in Japan dynamically affect smoking prevalence. [44] extended this analysis to the general community, exploring how smoking behaviors spread through social networks. Both studies underscore critical yet often overlooked factors in tobacco control policymaking.

2.3 Dynamic Retail Pricing

Neighboring retailers can intricately influence retail pricing strategies to maintain competitiveness and market responsiveness. Studies highlight that retailers often use dynamic pricing, adjusting their prices based on real-time data from competitor activities to attract price-sensitive consumers and optimise sales [52, 53, 54]. Localised pricing strategies are crucial, where retailers set prices based on local market conditions and competitor pricing to maximise profitability [55].

Another finding from a study on retail prices and point-of-sale tobacco displays in the UK supports the notion that retail prices among neighboring retailers are often similar. [56] showed that cigarette prices varied significantly between brands but were relatively consistent within the same brand across different retailers. For example, the mean price of 20-pack cigarettes was £5.50, with prices clustering around certain modes, reflecting a competitive pricing strategy to attract price-sensitive customers.

This research project also explores pricing due to interactions between retailers to accommodate the dynamic nature of retail pricing. A network structure will be embedded in the model, linking retailers based on the proximity (location). In addition to dynamic pricing to maintain gross profits, the model will incorporate pricing adjustments by calculating the weighted average of neighbors' prices based on their distances.

Chapter 3

Model Design

3.1 Environment

3.1.1 Environment Structure

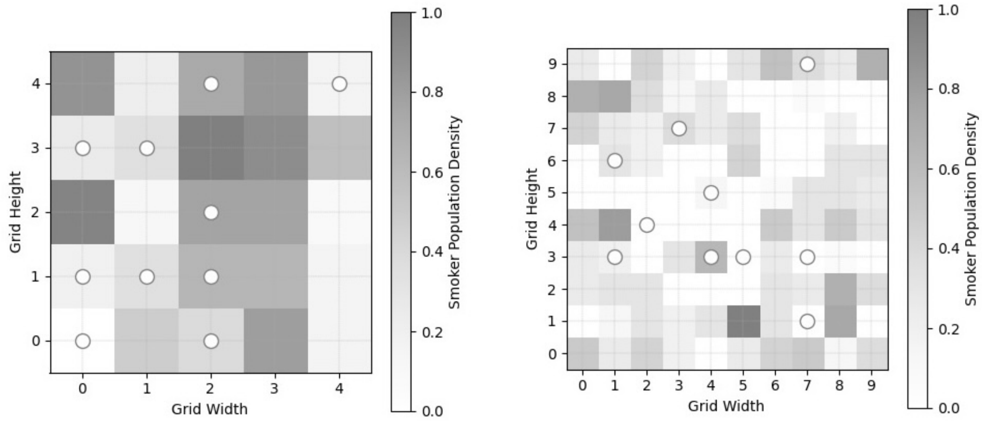

Figure 3.1: Model-generated population and retailer density. Left: 5 x 5 grid, 0.19 smoking prevalence, 10 retailers. Right: 10 x 10 grid, same prevalence and retailers.

The environment in this simulation is structured as a grid[1] representing the streets within city blocks. Streets within the grid are used by adult smoker agents for traveling between locations such as houses, workplaces, and tobacco retailers. The simulation environment consists four distinct types of areas: urban, rural, least-deprived, and most-deprived. Each type of area has unique attributes tailored to reflect specific conditions based on empirical data from data zones[2] in Scotland. Each area consists of an equal

[1] Similar to Tobacco Town model in [49, 50], which realistically portraying a city landscape [57, 58] where various entities interact and move

[2] Data zones are the core geography for the dissemination of small area statistics in Scotland, designed to provide a consistent and stable geography for statistical analysis [59].

population size[3] but varies in spatial extent, reflecting different population densities. For instance, urban areas typically have a smaller spatial extent with a higher population density, whereas rural areas cover larger spatial extent with lower population density [60].

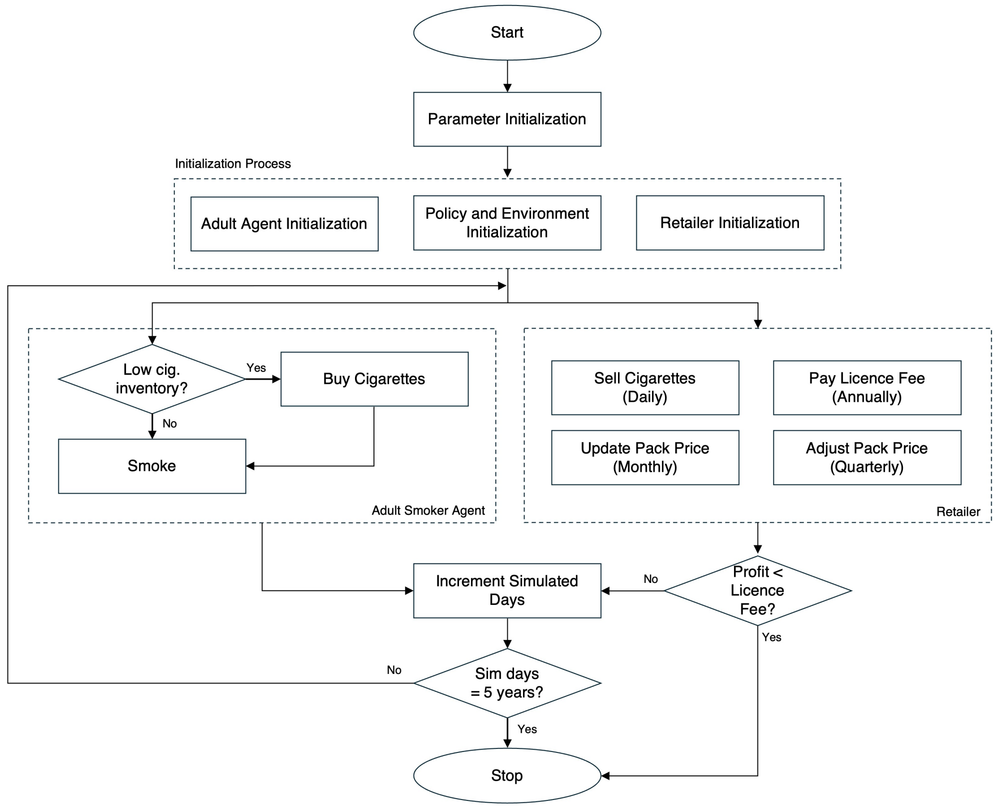

Figure 3.2: Flowchart of the simulated environment

Entities within the model are randomly allocated within the grid according to the empirical data of their respective area types. Various types of tobacco retailers are placed within the grid based on retailer density data for each area, ensuring that the density and types of retailers accurately reflect actual market conditions. Adult agents, both smokers and non-smokers, are generated according to population proportion data. During initialisation, each agent is assigned a home and workplace, which are generated according to model parameters and randomly positioned within the grid.

The flowchart in (Figure 3.2) illustrates the simulation model process. After the initialisation process, on each simulated day, smoker agents travel from home to their workplace and make purchase decisions based on their consumption level and inventory. Retailers, in addition to selling cigarettes to smokers, perform several additional actions: paying the licencing fee annually, updating pack prices based on neighboring prices

[3] The total population size for each type of area in this simulation is 10,000.

monthly, and adjusting pack prices quarterly based on expected annual gross profit. Retailers will stop selling tobacco if they have a lower gross profit than the annual licencing fee. The simulation advances by incrementing simulated days until it reaches five years, at which point it stops.

3.1.2 Environment Properties

Table 3.1: Properties of Environment

Property	Types, Description, and Updates	initialisation	Sources
Adult proportion	Positive real number. Proportion of adult agent (age 35-44) being simulated. Static.	0.125	[61]
Grid	2D grid. Represents streets within city blocks (spatial model of the city environment). 10 grid represents 1 km. Static.	Based on simulated area type	Empirical data (Table A.1)
Total population	Positive integer. Total population for simulated area. Static.	20000	Table A.1 and [59]
Retailers density	Positive real number. Total number of retailers in the simulated area per km^2.	Based on simulated area.	Empirical data (Table A.6)
Prevalence	Positive real number. Smoking prevalence for adult agent in population.	Based on simulated area.	[62]
Houses density	Positive real number. Average total number of homes per data zone. Static.	Based on simulated area.	Empirical data (Table A.1)
Workplaces density	Positive real number. Average total number of workplaces per km^2. Static initialisation.	Based on simulated area.	Empirical data (Table A.1)
Transport proportions	Positive real number. Proportion of people using that mode of transport (car, public transport, and others). Static.	Based on simulated area.	Empirical data (Table A.1)
Policy	Policy class. See Section 3.2.	Based on scenario.	-

3.2 Policy

The Policy class within the simulation mimics real-world implementations of tobacco licence fee policies. This class encapsulates various fee structures that may be imposed on retailers, reflecting the diversity of regulatory approaches observed globally [2, 5]. In the simulation, the licencing fee is charged annually at the end of the year. Retailers are required to pay this fee from their gross profits. Similar to the work of Valiente et al. [5], this study also incorporates the behavior of retailers where, if their gross profit falls below the annual licence fee, they decide to cease selling tobacco.

Policy Properties

Table 3.2: Properties of Policy

Property	Types and Description	initialisation	Sources
Base fee	Positive real number. Amount of initial licence fee. Static initialisation.	30% from median gross profit.	[5]
Fee structure	Categorical. Amount of initial licence fee. Static initialisation.	Flat, volumetric, urban/rural.	Determined [5]
Annual increment (%)	Positive real number. Annual increment percentage for licence fee. Static initialisation.	20% or 50%.	Determined

Policy Scenarios and Experiments

The simulation encompasses three fee structures (universal, volumetric, and rural/urban), each applied under two annual percentage increase scenarios: 20% and 50% (to represent low and high increase). This results in six distinct policy tests applied to various area types within the simulation environment (urban, rural, least-deprived, and most-deprived areas). Table A.7 presents the comprehensive range of all policy tests.

3.3 Tobacco Retailer Agent

3.3.1 Nature of the Agent

Retailers in this research project represent tobacco retailers, serving as one of the primary subjects within the model. Retailers are categorised into two main categories: large and small retailers (the distinctions between them are explained in Section 3.3.3). Each retailer operates within a defined geographic location and possesses distinct attributes informed by empirical data (see Table 3.3).

To capture the dynamic nature of retail pricing, we incorporate the DeGroot model [63], wherein a retailer's price is influenced by a weighted average of neighboring retailers' prices based on their distance. This scheme allows us to simulate the competitive pricing strategies that can impact a retailer's profitability and consumer behavior. Retailers adjust their prices not only in response to licencing fees [5, 43] but also to maintain competitiveness within their local market [53, 55].

3.3.2 Agent Properties

Table 3.3: Properties of Tobacco Retailer

Property	**Types, Description, and Updates**	**initialisation**	**Sources**
Retailer type	Categorical. Assigned based on empirical data. Different types include large retailers and small retailers.	Based on retailer distribution in simulated area.	Empirical data (Table A.1)
Location	Tuple [int x, int y] constrained within the bounds of the grid. Static.	Randomly assigned to a cell on the grid.	Determined
Price pack	Positive real number. Pack price for cigarettes. Updated dynamically based on sales volume and neighbor's prices.	Truncated $N(\mu_{\text{price}}, \sigma^2_{\text{price}})$ for each area type.	Empirical data (Table A.6)
Cost per pack	Positive real number. Initial cost per pack of cigarettes. Static.	Truncated $N(\mu_{\text{cost}}, \sigma^2_{\text{cost}})$ for each area type.	Empirical data (Table A.6)
Gross profit	Real number. Yearly gross profit (GBP). Updated dynamically based on sales and costs.	0	Determined (validated)
Sales volume	Positive integer. Yearly sales volume in the sticks. Updated dynamically based on sales.	0	Determined (validated)

3.3.3 Agent Actions

Each step in the simulation represents a day during which retailers can undertake various actions critical to their operation and adaptation within the market.

Sell Cigarettes

In each simulated day, retailers can sell cigarettes to adult smokers based on smokers' demand, which is determined by their daily consumption and inventory levels. When this action occurs, the retailer updates its sales records and calculates the impact on its financial metrics. The sales and quarterly sales volumes are increased, and the gross profit is updated. The gross profit is calculated as the difference between the pack price minus value added tax and the cost per pack, multiplied by the number of packs sold.

Adjust Pack Price

Retailers simulate their responses to the licencing fee by dynamically adjusting the price of cigarette packs on a quarterly basis. This adjustment is informed by the sales volume from the previous quarter and the projected annual gross profit. This action begins by predicting the annual gross profit using the formula:

$$E_{gp} = G + \left(\frac{Q_i \times Q_r}{20}\right) \times (P - C) \tag{3.1}$$

where E_{gp} is the predicted annual gross profit, G is the current gross profit, Q_i is the quarterly sales volume, Q_r is the number of quarters remaining in the year, P is the pack price after value added tax reduction, and C is the cost per pack.

The annual licencing fee F is calculated using the model's policy function. If the predicted annual gross profit E_{gp} is less than the annual fee F, the retailer calculates the additional revenue needed R to cover the fee and maintain a target gross profit margin:

$$R = M \times (F - E_{gp}) \tag{3.2}$$

where M is the random multiplier (ranging between 1.0 and 1.1). The retailer may decide to increase the pack price to generate this additional revenue, with the new price calculated as $P_{new} = R/\left(\frac{Q_i \times Q_r}{20}\right)$ and the pack increase as $\Delta P = P_{new} - P_{current}$.

To ensure a realistic price adjustment and prevent sudden changes, the retailer caps the maximum increase to a percentage α of the current pack price using $\Delta P = \min(\Delta P, \alpha \times P_{current})$ where α is set to 0.05 (or 5%). If the decision is made to increase the price, the pack price is updated, and the proportion of the fee passed on to customers through price increases is recorded.

Pay Licence Fee

Retailers need to pay a licencing fee annually. To simplify the process, this fee is charged at the end of the year for all retailers. The amount is determined using the model's policy function and deducted from the retailer's gross profit. The remaining gross profit is then recorded in the model's profit data. This action also resets the annual metrics (sales volume and gross profit), preparing the retailer for the next annual cycle.

The model incorporates two distinct behaviors for retailers. For small retailers, if the gross profit falls below zero, they cease selling tobacco and are removed from the simulation. In contrast, large retailers remain unaffected by the fee schemes; they continue to sell cigarettes regardless of the financial impact of the fees. This differentiation is supported by evidence suggesting that large retailers can absorb the financial impact of tobacco fees more effectively with their diversified business models and higher overall profits [64]. Existing research substantiates this assumption, suggesting that large retailers are better equipped to manage regulatory costs due to their diversified revenue streams and greater economic resilience [65].

Update Pack Price

Retailers can adjust their cigarette pack prices based on the prices of neighboring retailers, simulating competitive pricing dynamics within the market. This action is performed on a quarterly basis.

The action begins by identifying neighboring retailers within the network. For each neighboring retailer, the model calculates the inverse of the distance (weight) between them, which serves as the weight for the price adjustment. The pack prices of the neighboring retailers are then aggregated using a weighted average formula:

$$P_{\text{weighted}} = \frac{\sum_{i=1}^{n} P_i \times w_i}{\sum_{i=1}^{n} w_i} \tag{3.3}$$

where P_{weighted} is the weighted average price of the neighboring retailers, P_i is the pack price of the i-th neighboring retailer, w_i is the weight (inverse distance) associated with the i-th neighboring retailer, and n is the total number of neighboring retailers.

If the retailer's current pack price is below/above the weighted average price, the retailer adjusts its pack price towards the weighted average[4]. The new pack price P_{new} is calculated as:

$$P_{\text{new}} = P_{\text{current}} + \alpha \times (P_{\text{weighted}} - P_{\text{current}}) \tag{3.4}$$

where P_{current} is the retailer's current pack price and α is the increase and decrease rate set to 0.1. The retailer will only lower the price if the predicted annual profit after the price adjustment is expected to cover the annual licencing fee. This prediction involves calculating the additional profit from the price reduction for the remaining months in the year:

$$\Pi_{\text{additional}} = m_{\text{remaining}} \times S_{\text{monthly}} \times (P_{\text{new}} - C) \tag{3.5}$$

where $m_{\text{remaining}}$ is the number of remaining months, S_{monthly} is the average monthly sales, and C is the cost per pack.

If the predicted annual profit, $\Pi_{\text{predicted}} = G + \Pi_{\text{additional}}$ (current gross profit G plus additional profit $\Pi_{\text{additional}}$) after the price reduction, is greater than or equal to the

[4] Retailers with higher sales volumes (gross profits that remain larger than the annual licence fee) will not raise prices to avoid the risk of losing customers due to price increases.

annual fee, the retailer will lower the pack price to the new calculated price. Additionally, if the retailer decides to increase or decrease the pack price, the favorite retailer of the adult agents will be updated based on the latest pack price.

3.3.4 Agent Interactions

Interaction with Other Retailers

Retailers interact with other retailers directly within the proximity network when updating pack prices. The network is based on proximity, meaning retailers are influenced by the prices of nearby competitors. This choice reflects real-world scenarios where geographic closeness impacts competitive dynamics [66]. By using a proximity-based network, the model ensures that the influence of local competition is accurately represented, capturing the essence of regional market interactions [67]. The proximity network is formed using the method explained in Appendix A.4.

Interaction with Adult Smoker Agents

Retailers interact directly with adult smoker agents when these agents decide to buy cigarettes. This interaction involves the smoker agents evaluating their preferred retailer based on cigarette pack price and other indirect costs (see Section 3.4). The retailer's sales volume and gross profit are then updated accordingly.

Dynamic Updates for Ceasing Tobacco Sales

Small retailers will stop selling tobacco if their gross profit falls below the annual licencing fee. This decision ensures that retailers who are not financially viable under the current regulatory and economic conditions are accurately represented in the model. When a retailer ceases tobacco sales, the model removes the retailer from the list of active tobacco sellers and updates the network of preferred retailers for adult smoker agents.

Interaction with Policy Environment

Retailers interact directly with the policy environment by paying licencing fees. The model incorporates policy functions that calculate annual licencing fees based on specific criteria (see Section 3.2). Retailers need to adjust their pricing strategies and financial planning to accommodate these fees.

3.4 Adult Agent

3.4.1 Nature of the Agent

The adult agent in this simulation represents individuals aged 35-44. This age group is chosen due to several key factors. Individuals in this demographic are in their prime working years, significantly influencing economic activities and household decisions. Research shows that substance use, including smoking, impacts labor force participation and income within this age group, suggesting that interventions here can have substantial economic benefits [68]. Middle-aged adults are also critical targets for smoking cessation programs due to their established habits and potential for long-term health improvements [69]. Additionally, reducing smoking prevalence in this group can alleviate the economic burden on healthcare systems, as they are likely to incur high medical costs related to smoking-related diseases [70].

The adult agents are modeled with various attributes and behaviors that reflect real-world characteristics of individuals in this age group. They are categorised as smokers, non-smokers, or quitters. Smokers in the simulation purchase and consume cigarettes regularly, non-smokers do not engage in tobacco use, and quitters are former smokers who have ceased tobacco consumption (see Section 3.4.3).

Agents are generated for each simulation run based on the empirical data for each type of area (see Table 3.4). To simulate the aging process of the agents, their ages are incremented daily within the simulation. Agents who surpass the 35-44 age range are subsequently removed from the model. New agents are introduced into the model to account for the dynamic addition of individuals turning 35. This process is facilitated by Previous Age Agent, which ensures a steady influx of agents into the target age group. Further details about the Previous Age Agent can be found in the Appendix A.7.

3.4.2 Agent Properties

Table 3.4: Properties of Adult Agent

Property	**Types, Description, and Updates**	**initialisation**	**Sources**
Age	Integer. Age of the agent in days, representing individuals aged 35-44. Incremented daily	Assigned upon agent creation.	Determined and Empirical data (Table A.1)

Continued on next page

Table 3.4 – *Properties of Adult Agent (continued)*

Property	Types, Description, and Updates	initialisation	Sources
Smoking status	Categorical (smoker, non-smoker, & quitter). Updated based on smoking consumption.	Assigned based on empirical smoking prevalence data.	Empirical data (Table A.1)
Home location	Tuple [int x, int y] constrained within the bounds of the grid. Home location of the agent within the grid. Static initialisation.	Randomly assigned.	Determined
Work location	Tuple [int x, int y] constrained within the bounds of the grid. Work location of the agent within the grid. Static initialisation.	Randomly assigned.	Determined
Wage	Positive real number. Weekly wage of the agent, affecting purchasing power. Static initialisation.	Randomly assigned (income distribution).	Empirical data (Table A.1)
Smoking rate	Integer. Number of cigarettes consumed per day. Updated based on price elasticity function (see Section 3.4.3).	Randomly assigned (smoking rate distribution).	Determined and Empirical data (Table A.1)
Cigarette inventory	Integer. Number of cigarettes the agent currently possesses. Static initialisation.	Randomly assigned from range [1, 50].	Determined
Transport mode	Categorical. Mode of transport used by the agent. Static initialisation.	Randomly assigned.	Empirical data (Table A.1)
Price elasticity	Real numbers. Price elasticity for the agent. Static initialisation.	Assigned based on type area.	Empirical data (Appendix A.6)
Favorite retailer	Retailer class. Agent's preferred tobacco retailer. Updated dynamically.	Assigned based on proximity & price.	Determined (Section 3.4.3)
Days without smoking	Integer. umber of days the agent has gone without smoking. Updated dynamically based on agent's decision.	0	Determined

3.4.3 Agent Actions

Choose Favorite Retailer

This action allows an agent to select their preferred tobacco retailer based on the total cost, which includes both the trip cost and the cost of cigarettes. The cigarette cost, $C_{\text{cigarette}}$, is calculated as the cost of the minimum number of packs needed to meet the agent's daily consumption, assuming a pack contains 20 cigarettes:

$$C_{\text{cigarette}} = \left\lceil \frac{Q_{\text{daily}}}{20} \right\rceil \times P_{\text{retailer}} \tag{3.6}$$

where Q_{daily} is the daily cigarette consumption of the agent, and P_{retailer} is the pack price at the retailer. For the trip cost, similar to [50], for each retailer in the model, agents calculate[5]:

$$C_{\text{trip}} = \left(\frac{\Delta d_{\text{retailer}}}{v} + \frac{1}{12}\right) \times w \times V + \left(\Delta d_{\text{retailer}} \times \frac{P_{\text{petrol}}}{e}\right) \tag{3.7}$$

where $\Delta d_{\text{retailer}}$ is the distance from the agent to the retailer[6], v is the average speed in kph, w is the hourly wage of the agent, V is the value of time parameter[7], P_{petrol} is the petrol price, and e is the average energy consumption per kilometer. The total cost, which combines the trip cost and the cigarette cost, is then stored for all retailers.

The agent then selects the favorite retailer based on the trembling hand process, similar to [50]. This selection mechanism introduces a realistic element of randomness in decision-making, considering that agents is not perfectly rational [71]. Details regarding the trembling hand process can be found in Appendix A.5.

In addition to the initialisation phase, choosing a favorite retailer is also triggered whenever there are changes in retailer conditions, such as updates to pack prices or the cessation of tobacco sales by certain retailers. When a new favorite retailer is assigned, the agent recalculates its smoking rate using the formula:

$$Q_{\text{daily}} = Q_{\text{daily}} \times (1 + \Delta C_{\text{total}} \times E) \tag{3.8}$$

where ΔC_{total} is relative increase in the total cost and E is the price elasticity parameter (see Appendix A.6). This adjustment recalibrates the agent's daily cigarette consumption based on the new total cost.

Buy Cigarettes

On each simulated day, agents can buy cigarettes with their favorite retailer based on their inventory. Initially, the agent calculates the number of packs to purchase based on their daily consumption and money available. This involves determining the number of packs and assessing how many can be afforded after considering the trip cost. The total cost is calculated, inclusive of the trip cost. Given that the agent possesses adequate funds, their inventory is updated with the newly acquired packs, and their available funds are reduced by the corresponding total cost. The detailed algorithm for this action can be seen in Algorithm 1.

[5] The term $\frac{1}{12}$ represents a 5 minute time cost to make cigarette purchase.
[6] Based on the Manhattan distance, see Equation A.1
[7] $v = 1$, similar to [50], implying that the agents equate the value of lost wages with the cost of cigarettes.

Smoke

Agents smoke according to their daily cigarette consumption rate. If they have enough inventory, their cigarette count is reduced by the number of cigarettes smoked, and their cumulative smoking metrics, including lifetime cigarettes smoked and total cigarettes consumed, are updated accordingly.

This model also incorporates a simple cessation mechanism. If the agent has no cigarettes to smoke, the days without smoking counter is incremented by one. If this counter reaches or exceeds certain days[8], the agent's smoking status is updated to 'quitter'. Using a simple cessation mechanism serves to streamline the model, thereby allowing a focus on economic behaviors and policy impacts rather than the complexities of social interactions.. While this simplification is a limitation, it is a strategic choice that helps maintain the model's tractability and focus. Although more complex cessation mechanisms considering social factors could provide deeper insights, they would also require significantly more data and computational resources, potentially complicating the analysis and interpretation of the economic and policy-focused aspects of the model.

3.4.4 Interaction with Other Agents

Interaction with Retailers

Agents interact directly with retailers when deciding to purchase cigarettes. This interaction is driven by the agent's cigarette inventory and consumption needs. The agent evaluates the cost of purchasing cigarettes from their favorite retailer, including both the pack price and the trip cost. If the agent has sufficient funds, they proceed with the purchase, updating their inventory and financial balance accordingly.

Interaction with Policy Environment

Agents interact indirectly with the policy environment. The policies implemented in the simulation affect the pack price of cigarettes at retailers, which in turn influences the agents' purchasing decisions and smoking behaviors. For example, increasing licencing fees for retailers can lead to higher pack prices, affecting the affordability of cigarettes for agents. This indirect interaction demonstrates how policy changes can cascade through the economic environment, ultimately impacting individual behaviors and consumption patterns.

[8] The value is set to 28 (four weeks).

Chapter 4

Model Validation and Sensitivity Analysis

Validation is one of the primary ingredients in the model development process. It assesses whether the model can accurately reproduce the behaviors of a real-world system [72]. Midgley et al. [73] emphasise that validation must be conducted on at least two levels: at the agent level (micro-validation) to align model parameters with empirical data for individual agents and at the system level (macro-validation) to ensure that the model's overall responses correspond to empirical data for the complete model. Volk et al. [74] define the first concept as *input validation*, the second as *output validation*, and the process of parameterising the system to enable such validation as *calibration*.

4.1 Input Validation

Input validation ensures that the fundamental structural, behavioral, and institutional conditions integrated into the model accurately replicate the primary aspects of the actual system [75]. This process is done by introducing the correct parameters into the model before running it. We derive confidence in the model by basing a significant portion of our assumptions and initial parameters in empirical data (reputable studies and governmental reports) and widely accepted theories.

The environment in the model is divided into four types of areas, informed by realistic data zones from the National Records of Scotland [76]. These areas include urban, rural, least-deprived, and most-deprived. Key parameters for each area type are derived from this data, including the average area of the data zone (which determines the grid size), average total population per data zone, household density, business density, and transport proportions. Adult proportion data is obtained from the National Statistics Publication for Scotland 2023 [77], while information on smoking prevalence and average cigarette consumption is sourced from the Scottish Health Survey 2022 [62]. Finally, the transportation mode, proportions, and average speed are obtained from Transport Scotland Statistics 2016 [78].

In each simulation, retailers are generated based on the spatial density of various types of retailers specific to each area type, utilising data from the Scottish Registry for Tobacco and Nicotine Vapor Products (Table A.6). The pack price and cost price distributions are informed by transaction data from electronic point-of-sale records in 2022, as used in the study by Valiente et al. [5]. Assumptions regarding retailer behavior, including the strategy of passing fees to customers and updating prices to reflect regional market interactions, are grounded in empirical studies cited in the Model Design Chapter.

Finally, adult smoker agents are generated for each simulation based on the smoking prevalence derived from the Scottish Health Survey 2022. [62] Each agent is assigned a weekly wage according to the wage distribution specific to each area type derived from Annual Survey of Hours and Earnings 2022 [79], a smoking rate based on Smoking Health Survey 2022 [62], and price elasticity informed by empirical data (Appendix A.6). When purchasing cigarettes, agents consider the total cost, including the pack price and the trip cost. This behavior aligns with fundamental behavioral and economic theories and studies demonstrating that individuals prefer to minimise costs and travel times when purchasing commodities [80].

4.2 Output Validation

[81] states that any model that aims to provide actionable decision support must be validated based on empirical data of the real-world system. To represent retailers from different environment settings, we employed two financial metrics for evaluation to our baseline model: annual sales volume[1] and gross profit.

In this project, most of the data obtained were categorised into four categories: urban most-deprived, urban least-deprived, rural most-deprived, and rural least-deprived. To align with our classification (urban, rural, most-deprived, and least-deprived), we aggregated these four categories by averaging their values. Initially, we made a straightfor-

[1] It is similar to validation process for Tobacco Town model by [46]

ward assumption by using simple averages. However, the simulations' output displayed a significant discrepancy with the historical sales volume and gross profit data (see Section 4.3). We then refined our approach by applying a weighted average calculation. The weighting was based on the population proportion grouped by Scotland's SIMD decile and six-fold urban/rural classification [82]. The weight parameters for each area are presented in Table 4.1, and the detailed weighting calculations are provided in Appendix A.10.

Table 4.1: Weight Parameters for Each Area Type

Area Type	**Weight Parameters**			
	Urban Most	**Urban Least**	**Rural Most**	**Rural Least**
Urban	0.556	0.444	-	-
Rural	-	-	0.250	0.750
Least-deprived	-	0.971	-	0.029
Most-deprived	0.939	-	0.061	-

The validation results[2] indicate that the average sales volume and gross profit from the model is consistent when compared to the average sales volume and gross profit data from 2022 (Figure 4.1 left). There is a consistent 25-27% discrepancy, with the model's output being lower; however, the proportion between the model's output and the empirical data aligns well. We identified several factors that could explain this difference. First, the discrepancy may be due to the assumption that each age group within the population contributes equally to the overall sales volume, potentially underestimating the contribution of the 35-44 age group. This aligns with the fact that average daily consumption increases with age [62]. Second, the difference could also result from individuals underreporting their daily cigarette consumption in surveys [84, 85, 86], causing the average sales in the model output to be lower than in historical data. We calculated that if we increase the average smoking rates by 25-27% for each area, the average sales and gross profit values will match the historical data. This adjustment falls within the range of rate discrepancies between smoking consumption and sales data in England, which can reach up to 36% [84].

This difference could be minimised by calculating the contribution proportion for each age group in the sales volume and adjusting daily average consumption according to the underreporting rate observed. However, due to time constraints and considering

[2] With the assumption that smokers can spend 30% of their wages to buy cigarettes. This assumption is derived from the cost of smoking based on household income for the lowest income quintile based on ASH Scotland 2023 [83]

the consistency in proportions between the model and historical data across all areas, we did not make further adjustments.

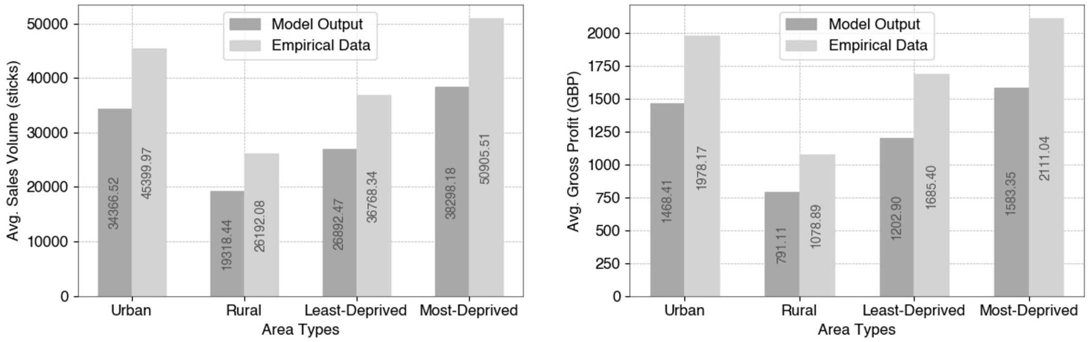

Figure 4.1: Left: Comparisons of the average sales volume from model output with historical data (2022). Right: Comparisons of the average gross profit from model output with historical data (2022). The output is specific to the 35-44 age group only.

In summary, based on the validation results (detailed table including other statistics, as seen in Table A.12), the model can effectively replicate the provided historical data. Discrepancies will always be unavoidable since the real world is always more complex than any artificial model. Given the consistency demonstrated across all metrics and different area types, the model can be considered complete and accurate. We are confident that the model will be practically applicable for further assessing licence fee policies.

4.3 Baseline Model Sensitivity Analysis

Sensitivity analysis is considered a good practice in the model verification process [87]. One of its roles is quantifying model output changes due to uncertainties in model parameters [88]. In this research, we conducted a sensitivity analysis to examine the sensitivity of the developed baseline model to variations in several parameters: total population, weight parameters, and trembling hand parameters. We performed the analysis using the one-factor-at-a-time (OFAT) technique, which involves choosing a nominal base setting and varying one parameter at a time while keeping others fixed [88]. The parameters used, along with detailed results of the sensitivity analysis, can be found in Appendix A.12.

Chapter 5

Analysis and Discussion

5.1 Model Simulation

We conducted 24 scenario experiments, which are combinations of various policy scenarios for four types of areas (detailed scenarios can be found in Table A.7). Each scenario was run for five years with 100 iterations. In each simulation scenario, the model generated a combination of individual data for each type of agent as well as aggregate data in the form of time series collected at the end of each month.

Table A.17 presents the base fee used in the simulation for each fee structure. These base fees are set based on a similar scheme by [5]. The 30% figure was chosen based on recommendations from one of the authors of [5] and previous research, where this value was found to have a noticeable effect compared to lower percentages.

The simulation also used two different levels of annual increment percentages. An annual increment of 20% represents a low to moderate increase in the licence fee, while an annual increment of 50% represents a more aggressive rate of increase.

5.2 Results

5.2.1 Number of Retailers

Figure 5.1 presents the estimated number of retailers remaining after the implementation of each licence fee scheme over a five-year period (Detailed numbers can be seen in Table A.18). The universal fee consistently ranked lowest in the number of retailers in rural areas up to the 4th year compared to other fee schemes (i.e., in the 4th year, the implementation of the universal fee with an annual increment of 50% in rural areas led to a decrease of 49% of retailers, lower compared to the volumetric scheme at 72%, and the urban/rural scheme at 52%. These trends were consistent throughout the first four years for all annual increment levels). Meanwhile, urban areas consistently maintained the second lowest position after the urban/rural scheme for the first four years (i.e., 0-2% lower compared to urban areas implementing the urban/rural scheme). An annual increment of 50% consistently resulted in a more significant reduction in retailers than an annual increment of 20%. More aggressive increment schemes could reduce the number of retailers by 10% (13%) in urban (rural) areas and by 12% (10%) in least-deprived (most-deprived) areas. For the same annual increment value, the number of remaining retailers was much smaller in rural areas (i.e., 54% with a 20% annual increment in the 5th year vs. 59% in urban areas) and in most-deprived areas (i.e., 54% with a 20% annual increment in the 5th year vs. 72% in least-deprived areas).

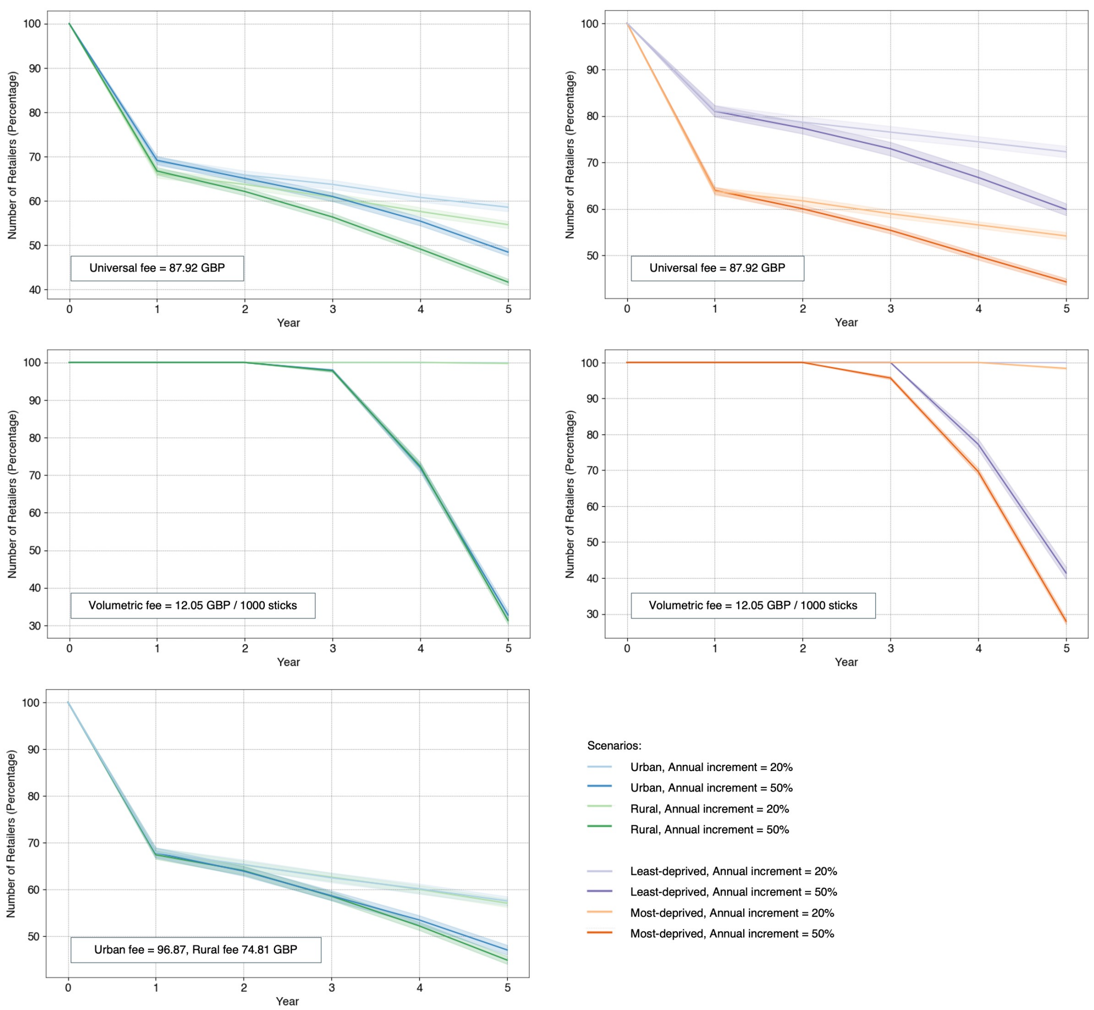

Figure 5.1: Estimated number of retailers remaining after the implementation of each licence fee scheme (universal, volumetric, and rural/urban) over a five-year period.

In contrast, the volumetric fee demonstrated a different pattern of retailer reduction. This scheme did not decrease the number of retailers until the 5th year for an annual increment of 20% and the 3rd year for an annual increment of 50%. The 20% annual increment scheme did not cause a significant reduction, with 98-100% of retailers remaining in the 5th year. Conversely, the 50% annual increment could significantly reduce the number of retailers starting from the 3rd year and could result in the fewest retailers in the 5th year compared to other fee schemes (i.e., in the 5th year, the implementation of the volumetric fee with a 50% annual increment in urban areas left 33% of retailers, lower compared to the universal scheme at 48%, and the urban/rural scheme at 47% for the same year, area, and annual increment). Similar to the universal fee, the volumetric scheme resulted in different proportions of retailers in urban vs. rural areas and least-deprived vs. most-deprived areas (i.e., for a 50% annual increment from the 3rd year onwards, rural areas had 0.3-1% fewer retailers compared to urban areas, while most-deprived areas had 5-14% fewer retailers compared to least-deprived areas). We observed a very small difference between urban and rural areas because the median profit per 1,000 sticks in both areas is not significantly different from the median profit per 1,000 sticks across all areas.

The urban/rural scheme showed a similar pattern of retailer reduction with the universal fee. However, unlike the universal fee, this scheme did not demonstrate significant differences between urban vs. rural areas and least-deprived vs. most-deprived areas (i.e., the difference between areas at the same level of annual increment was only around 0-2%, much smaller compared to the universal fee, which showed a difference of about 2-7%). Additionally, like other fees, an annual increment of 50% led to a much more significant reduction in the number of retailers compared to an annual increment of 20%. By the 5th year, there was a difference of about 12% between the two annual increments across areas based on urbanicity and deprivation.

5.2.2 Gross Profit Distributions

Figure 5.2 illustrates the comparison of changes in gross profit distributions among retailers in different types of areas following the introduction of three different fee structures in the first year. The baseline model distributions exhibit a positive skew across all area types and each fee scheme results in different distributional changes. The universal fee shifts the distribution to the left, reducing the median of the distribution while maintaining the baseline model's shape. The urban/rural fee demonstrates a similar pattern to the universal fee. In contrast, the volumetric fee produces a slightly different effect. In addition to shifting the median gross profit downward, the distribution becomes more compressed than the baseline model. According to [5], this phenomenon is called the "squeeze effect," indicating a reduction in the number of retailers experiencing negative gross profits. The patterns observed in the initial year are consistent with the patterns generated by [5], which further validates our developed model.

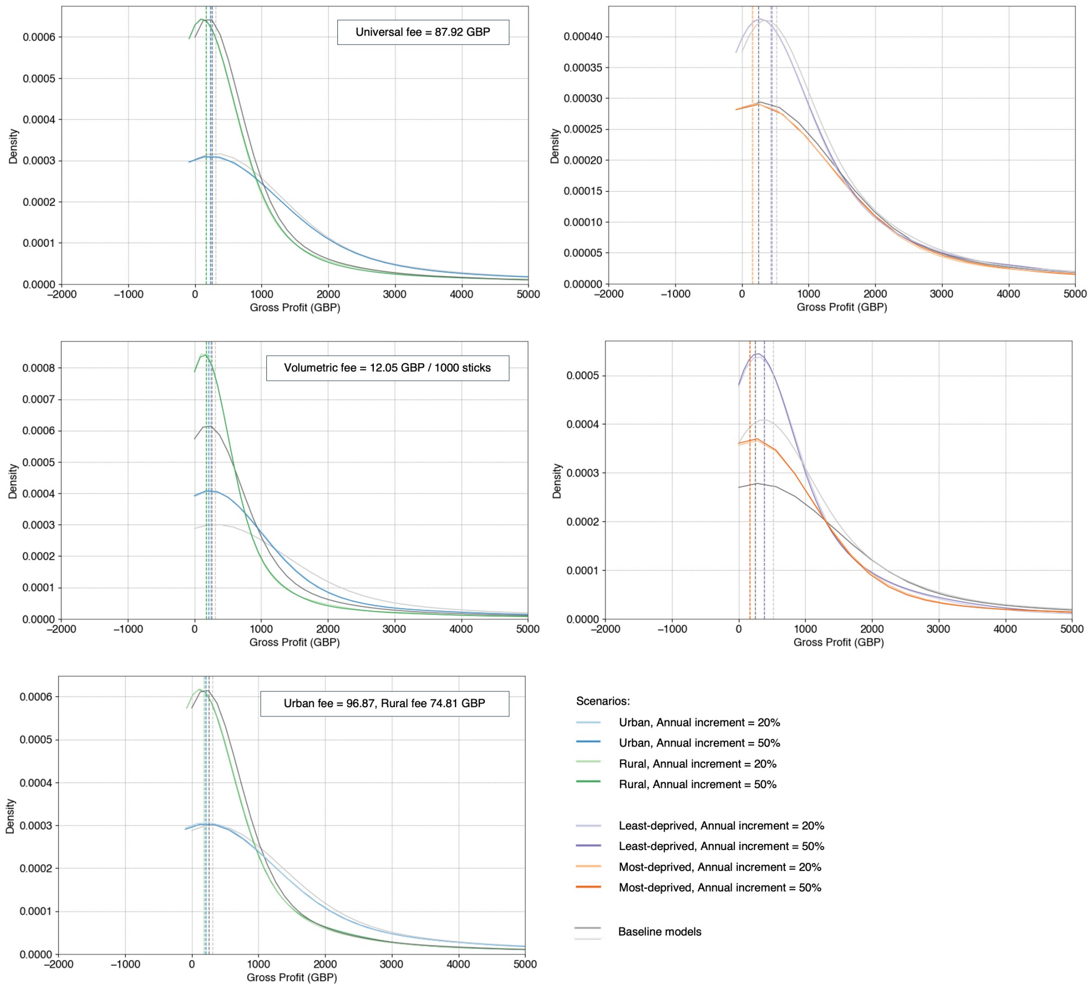

Figure 5.2: Impact of licence fee schemes on the distribution of gross profits among retailers in the first year.

One interesting aspect was the change in gross profit distributions in subsequent years (Figure 5.3). Under the universal fee scheme, the median gross profit consistently shifted to the right (increased) over the years for all area types and levels of annual increment. The shift occurred due to the disproportionate impact of the increased licence fees on retailers with lower sales than those with more significant sales volumes. Retailers that remained operational also gained additional customers from those retailers who decided to stop selling tobacco. This was further demonstrated by the trend in average sales volumes among retailers. For instance, for an annual increment of 50%, the average sales of retailers in urban areas reached around 35,000 sticks in the first year. This value consistently increased over the years, reaching an average sales volume of up to 62,000 sticks by the 5th year (details in the top left of Figure 5.4). Moreover, this gross profit trend can also be attributed to the relatively constant average total sales throughout consecutive years (Figure 5.4, top right). We observed that the consistency in total sales was influenced by consistent consumption patterns, indicated by the average smoking rates among smokers, which did not experience significant changes over the years (detailed discussion regarding consumption patterns can be found in Section 5.2.3). We also found a similar trend in the median gross profit for the urban/rural fee.

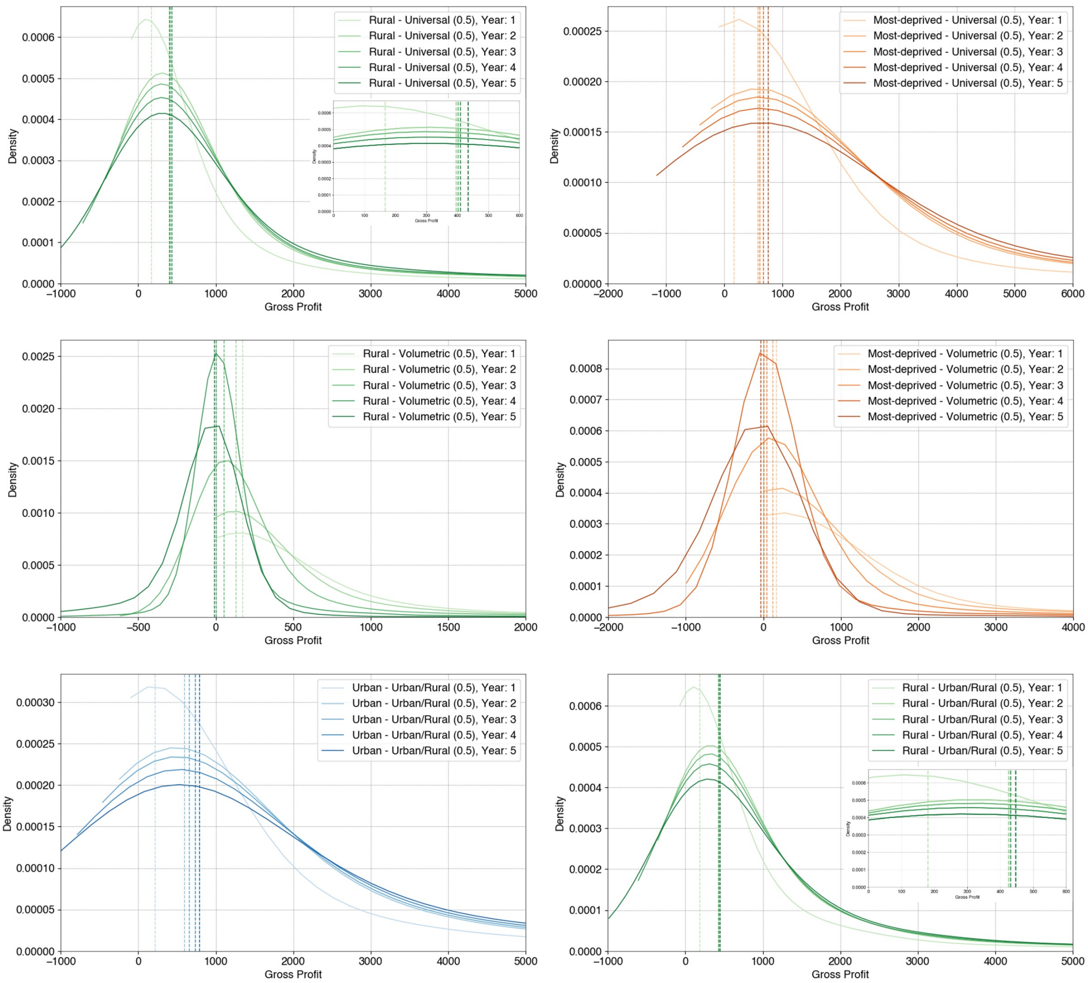

Figure 5.3: Impact of licence fee schemes on the distribution of gross profits among retailers for the first five years (We provide a zoom-in on several graphs).

Conversely, the volumetric fee consistently led to a declining median gross profit every year. For example, in most-deprived areas with an annual increment of 50%, during the first and second years, there was no reduction in the number of retailers, and the licence fees had an equal impact on retailers with both lower and higher sales volumes. This resulted in a squeeze effect on the gross profit distributions. In the third year, this squeezing effect continued, accompanied by a rather insignificant decline in the number of retailers.

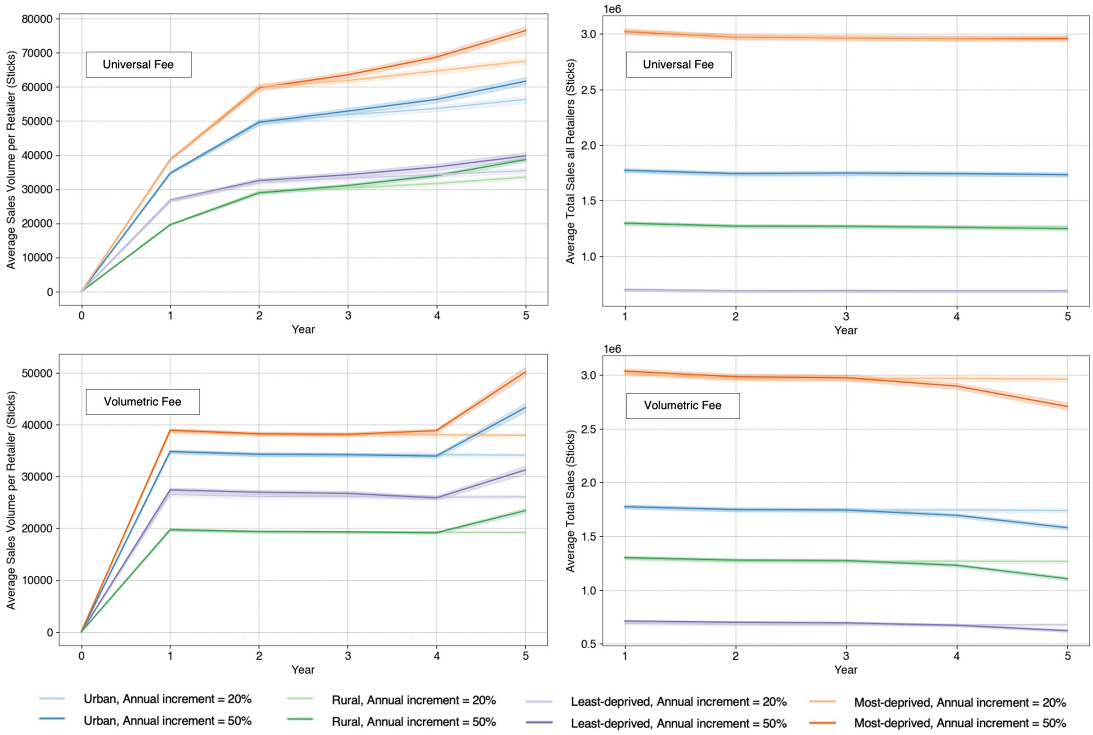

Figure 5.4: Average sales volume per retailer and total sales volume for all retailers across all levels of annual increment. Top left: Average sales volume for the universal fee. Top right: Total sales volume for the universal fee. Bottom left: Average sales volume for the volumetric fee. Bottom right: Total sales volume for the volumetric fee.

In the fourth and fifth years, although there was a significant reduction in the number of retailers, which increased the average sales volume (i.e., in the fourth and fifth years in the most-deprived area with a 50% annual increment, the average sales volume increased by 1,000 and 12,000 sticks compared to the third year. Figure 5.4, bottom left), we also observed a decrease in the overall average total sales (i.e., in the fourth and fifth years in the most-deprived area with a 50% annual increment, the total sales volume decreased by 78,000 and 267,000 sticks compared to the third year. Figure 5.4, bottom right). This was driven by changes in the consumption patterns of smokers (detailed discussion in Section 5.2.3). Furthermore, unlike the universal fee, the increasing licence fee in this scheme caused an equal impact on all retailers. This resulted in the median gross profit consistently declining across the years. All details related to the median gross profit for all area types and fee structures can be found in Table A.19.

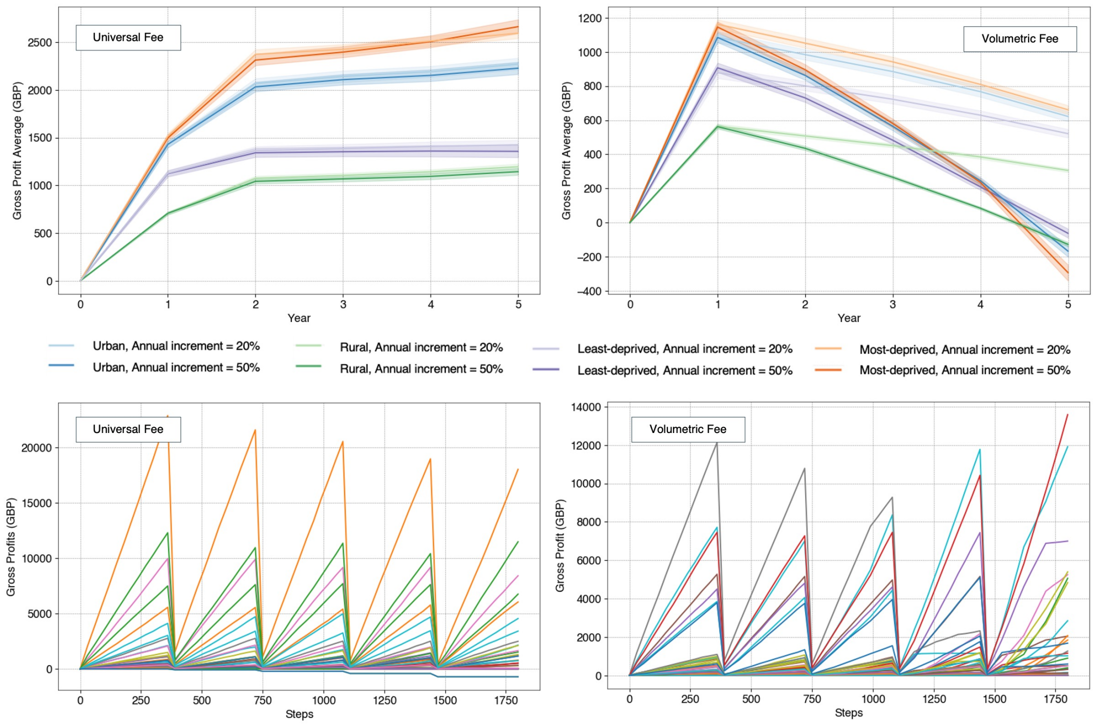

Figure 5.5: Top: Average gross profit of all retailers under universal (left) and volumetric (right) fees. Bottom: Gross profits per retailer for universal (left) and volumetric (right) fees from a single sample iteration. The bottom figure illustrates that the universal scheme disproportionately impacted low-sales-volume retailers (with a decreased density of low-profit retailers over time), while the volumetric scheme treated all retailers equally.

5.2.3 Consumption Patterns

Table 5.1: Average Smoking Rates

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Universal (20%)				
Year 1	12.152	11.849	10.842	13.473
Year 5	12.133 (-0.16%)	11.82 (-0.24%)	10.765 (-0.71%)	13.412 (-0.45%)
Universal (50%)				
Year 1	12.208	11.876	10.91	13.488
Year 5	12.092 (-0.95%)	11.691 (-1.56%)	10.851 (-0.54%)	13.411 (-0.57%)
Volumetric (20%)				
Year 1	12.229	11.79	10.892	13.38
Year 5	12.229 (0.00%)	11.784 (-0.05%)	10.892 (0.00%)	13.342 (-0.28%)
Volumetric (50%)				
Year 1	12.346	11.745	10.973	13.471

Continued on next page

Table 5.1 – *Average Smoking Rates (continued)*

Parameter	**Urban**	**Rural**	**Least-Deprived**	**Most-Deprived**
Year 5	10.482 (-15.11%)	9.581 (-18.43%)	9.308 (-15.16%)	11.47 (-14.85%)
Urban/Rural (20%)				
Year 1	12.233	11.84	-	-
Year 5	12.193 (-0.33%)	11.822 (-0.15%)	-	-
Urban/Rural (50%)				
Year 1	12.226	11.809	-	-
Year 5	12.157 (-0.56%)	11.626 (-1.55%)	-	-

Table 5.1 presents the trend in average smoking rates for adult smokers in all types of areas in the first and fifth years. The universal fee with a 20% annual increment had the least significant impact, with smoking rates decreasing by only 0.16-0.71% by the final year. In contrast, an annual increment of 50% could reduce the smoking rate by 0.54-1.56%. The implementation of this scheme had a disproportionate impact, with higher reductions occurring in rural and least deprived areas. On the other hand, the volumetric scheme had a significantly different impact with a more aggressive annual increment. An annual increment of 50% could reduce daily cigarette consumption by 14.85-18.43%. Similar to the universal fee, the greatest impact occurred in rural and least-deprived areas, with reductions of 18.43% and 15.16%, respectively. The urban/rural fee scheme had a similar impact to the universal fee (i.e., the reduction for all areas and level annual increments was less than 1% in the fifth year except for rural areas with 1.55% reduction).

Table 5.2: Prevalence Data

Parameter	**Urban**	**Rural**	**Least-Deprived**	**Most-Deprived**
Universal (20%)				
Year 1	0.160	0.119	0.070	0.250
Year 5	0.160 (0.00%)	0.119 (0.00%)	0.070 (0.00%)	0.250 (0.00%)
Universal (50%)				
Year 1	0.160	0.120	0.070	0.249
Year 5	0.160 (0.00%)	0.117 (-2.50%)	0.070 (0.00%)	0.249 (0.00%)
Volumetric (20%)				
Year 1	0.160	0.120	0.070	0.251
Year 5	0.160 (0.00%)	0.120 (0.00%)	0.070 (0.00%)	0.251 (0.00%)
Volumetric (50%)				
Year 1	0.159	0.121	0.071	0.250
Year 5	0.150 (-5.66%)	0.109 (-9.92%)	0.064 (-9.86%)	0.241 (-3.60%)

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Table 5.2 – *Prevalence Data continued*

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Urban/Rural (20%)				
Year 1	0.160	0.120	-	-
Year 5	0.159 (-0.63%)	0.119 (-0.83%)	-	-
Urban/Rural (50%)				
Year 1	0.160	0.120	-	-
Year 5	0.160 (0.00%)	0.118 (-1.67%)	-	-

The introduction of licence fees not only influenced the amount of daily cigarettes consumption but also affected the overall smoking prevalence (Table 5.2). We used rounding to three decimal places for prevalence and found that only the aggressive level of annual increment had a significant impact. Under the universal fee with a 50% increment, the largest reductions occurred in rural areas, with decreases of 2.5%. The volumetric scheme with a 50% annual increment had the greatest impact compared to other fee schemes. This scheme reduced smoking prevalence by 10% in rural and least-deprived areas, and by 4-6% in urban and most-deprived areas.

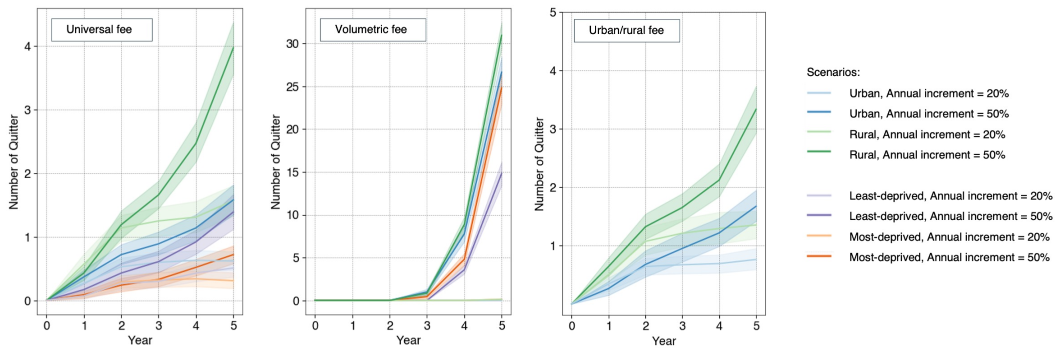

Figure 5.6: The comparison of quitters across various fee schemes and area types shows that a 50% annual increment consistently led to the highest number of quitters in each fee structure. Among these, the volumetric fee with a 50% annual increment resulted in the most quitters compared to other fee schemes.

One factor affecting the decrease in the average smoking rate and the decline in prevalence is the trip costs. Table A.20 compares the percentage increase in trip costs after the implementation of various licence fee schemes. When combined with the number of retailers, trip costs increase as the retailer density decreases (Figure 5.7). The most significant percentage increase in trip costs occurred in rural and least-deprived areas (i.e., for universal scheme in rural areas with a 50% increment, trip costs increased by 20%, significantly higher compared to 5% in urban areas. Likewise, trip costs in least-deprived areas are consistently higher than in most-deprived areas across all fee schemes). Similar to [46], we also found a nonlinear relationship between the number of retailers and the trip costs across all area types. When the number of retailers decreases, the reduction leads to a more significant increase in trip costs compared to when the number of retailers is relatively high. This explains why the increase in trip costs is more significant in rural and least-deprived areas than in urban and most-deprived areas.

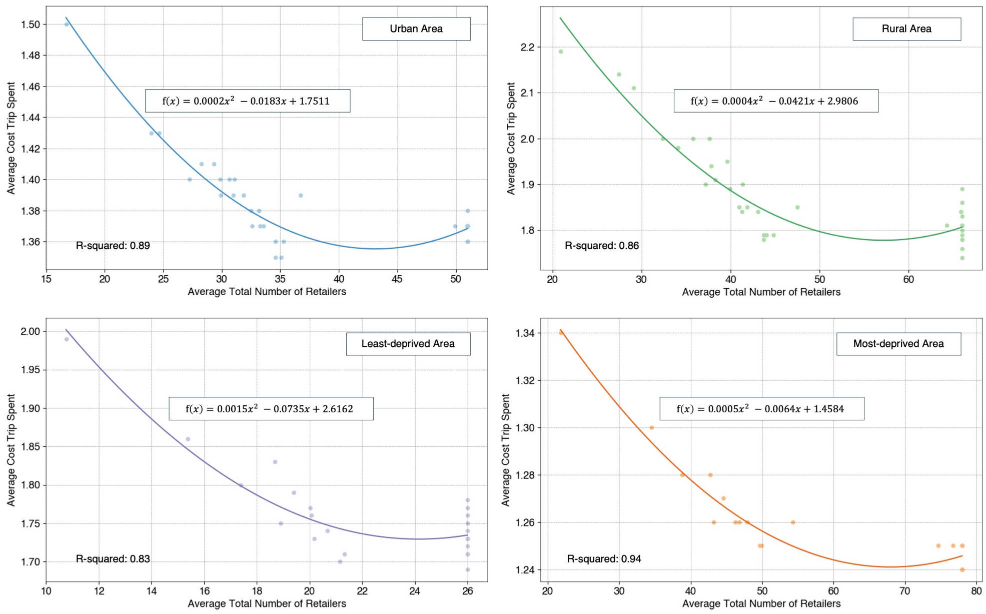

Figure 5.7: The relationship between the number of retailers and trip costs across area types is nonlinear. We fitted a polynomial function of degree 2, represented by the curved line. The R^2 values for each area type are shown at the bottom left of the graph.

In addition to trip costs, one of the factors contributing to the decrease in smoking rates and prevalence is the increase in cigarette pack prices (Figure 5.8). The universal fee scheme exhibited a sign of a price increase in the middle of the year. However, at the beginning of the year, pack prices decreased significantly. This indicates that retailers with lower sales volumes who tried to raise prices could not sustain their businesses and had to stop selling tobacco by the end of the year. Pack prices decreased to match the average pack prices of retailers with high sales volumes unaffected by the licence fees (who did not increase the prices). We observed the same pattern with the urban/rural fee scheme. In contrast, the volumetric fee scheme resulted in a consistently increasing trend in pack prices. Unlike the universal fee, the volumetric fee impacted almost all retailers, causing many to raise their pack prices simultaneously. Although there was a decrease at the beginning of the year due to some retailers closing, there were still retailers who increased their prices and continued to operate into the following year. Consequently, the pack prices experienced a steady annual increase.

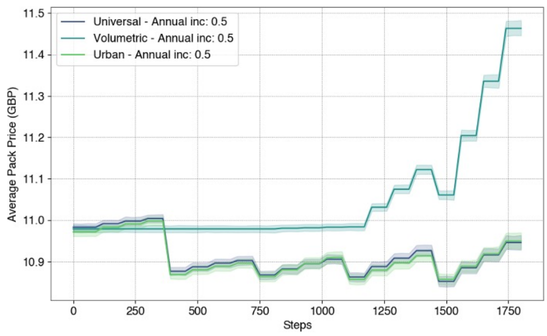

Figure 5.8: Example of the trend in increasing pack prices in urban areas with a 50% annual increment across all licence fee schemes.

5.3 Dynamic Retail Pricing Results

So far, retailers have only adjusted pack prices when their expected annual gross profits were lower than the annual licence fee. We also conducted simulations by implementing dynamic retail pricing, where retailers observe their neighboring prices. We performed simulations specifically for urban areas, implementing universal and volumetric schemes with all levels of annual increment (detailed results can be found in Appendix A.17).

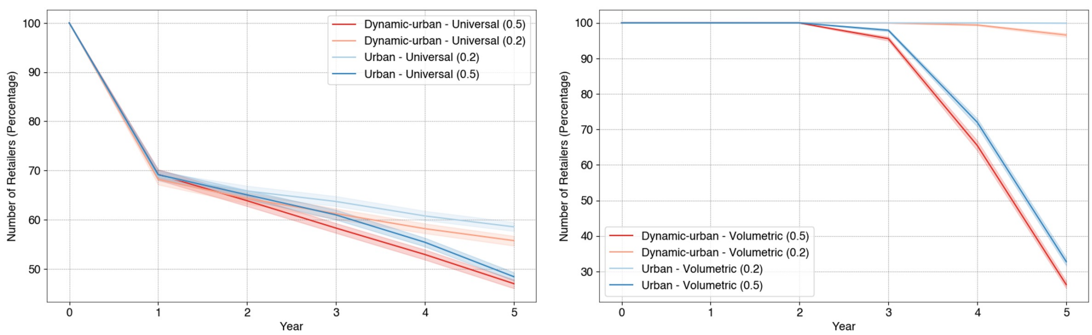

Figure 5.9: Comparison of the number of remaining retailers between simulations with and without dynamic retail pricing.

The universal scheme consistently resulted in 1-4% fewer retailers compared to the simulation without implementing dynamic retail pricing (Figure 5.9 left). This happened because retailers who initially had high pack prices and few or no customers attempted to lower their prices. The price reduction led to the shift of some customers from retailers with moderate sales volumes. Meanwhile, retailers with high sales volumes (low pack prices) were not significantly affected, as they did not adjust their prices. Consequently, the gross profits of retailers with moderate sales volumes decreased, causing them to stop selling tobacco. This reduction in retailer density also led to an increase in total costs (Figure A.4) for smokers, resulting in a reduction in the average smoking rate by up to 5% (Table A.21).

The volumetric scheme exhibited a similar pattern (Figure 5.9 right). However, unlike the universal fee, retailers in this scheme tended to lower prices during the first 2-3 years. With decreasing pack prices (Figure A.5) and constant cost per pack, the gross profit of some retailers declined, leading to more retailers stopping tobacco sales. Despite the initial downward trend in pack prices, smokers faced higher trip costs due to the decreasing retailer density. Consequently, total costs increased (Figure A.4), resulting in reduced overall consumption by up 28% compared to the simulation without dynamic retail pricing (Table A.21).

5.4 Discussion and Insights Gained

This discussion section is organised into several parts, referencing the research questions from Chapter 1.

What are the potential disparities in the impact of the increase of different licencing fee structures on retailers based on their location and size?

Using agent-based modeling, we assessed 24 scenarios encompassing universal, volumetric, and urban/rural schemes with two levels of annual increment across four different area types (urban, rural, least-deprived, and most-deprived). The simulation results revealed spatial differences in the impacts, both in terms of financial impacts on retailers and consumption patterns.

Universal schemes significantly reduced gross profits for retailers with low sales volumes, particularly in rural and most-deprived areas. Consequently, only retailers with high sales volumes could survive, as the licence fees did not impact them. On the other hand, the volumetric scheme had a more equitable impact on gross profits. This scheme imposed the highest fees on retailers with high sales volumes and the lowest fees on those with low sales volumes. Even retailers with no sales were able to sustain their operations. The urban/rural scheme had a similar impact to the universal scheme but did not disproportionately impact rural areas.

How does the increase of licencing fees over time influence the availability of different tobacco retailers based on their sociodemographic characteristics?

One of the most important findings from the simulation is the pattern of retailer density and changes in gross profits over the years. The universal and urban/rural schemes immediately impacted the number of retailers in the first year, leading to a linear reduction effect depending on the level of the annual increment fee. More aggressive annual increments resulted in a much steeper slope, causing a faster rate of retailer reduction. In the universal and urban/rural scheme, the median gross profits increased over the years, benefiting retailers with high sales volumes. In contrast, the volumetric scheme exhibited a delay effect, with a process ramp-up that caused the reduction in retailers not to occur immediately in the initial years of implementation. This scheme showed a nonlinear reduction effect, where the retailer reduction rate increased yearly (Figure 5.1 & Figure A.6). The implementation of higher annual increments significantly amplified the impact. Additionally, the median gross profits in the volumetric scheme consistently diminished, leading to a more equitable impact. However, this was accompanied by a decrease in consumption due to increased pack prices and trip costs.

This research project has successfully uncovered new key insights that expand upon previous studies. Policymakers can better understand the potential dynamics that may occur for retailers throughout the implementation of such schemes. The varying spatial impacts and effect patterns from each fee scheme can serve as critical inputs in designing effective policies. This is crucial for mitigating the potential domino effects that could impact wider society. Moreover, progressive licence fees can be seen as a viable instrument for medium to long-term policy strategies. Instead of introducing a high annual licence fee[1], which may face industry resistance [5, 2], a gradual fee increase could be implemented. The base fee and rate of increase can be carefully calibrated to align with the desired reduction patterns and targets. For example, a gradual licence fee increase could be combined with recommendations from Valiente et al. [5], who suggested a policy mix between urban/rural and volumetric fees in Scotland. Such a combination could serve as a balanced approach to implementing more equitable, measured policies without causing sudden significant financial impacts on retailers.

How might changes in the retail environment, induced by varying licencing fee structures, affect consumption patterns across communities?

We found that the implementation of increasing licence fees did not significantly impact consumption patterns. While a reduction in retailer density could lead to increased trip costs, this rise did not immediately result in a substantial change in consumption patterns. A decline in average smoking rates and smoking prevalence became noticeable only

[1] [5] found that the license fee required to reduce retailer density by 50% in Scotland is significantly higher compared to several other countries.

when accompanied by an increase in pack prices. However, significant changes in pack prices only occurred when implementing a volumetric scheme with an aggressive annual increment. Our analysis demonstrated that the volumetric scheme with an aggressive annual increment leads to the largest retailer reduction among the fee schemes.

Policymakers need to understand this dilemma. In defining a new licence scheme, careful consideration must be given to how dependent retailers are on tobacco sales and the overall impact on their businesses. This is especially important given the nonlinear relationship between trip costs and retailer density, which could have additional effects on communities in areas like rural and least-deprived regions with relatively low retailer density. While the primary goal is to improve public health by reducing tobacco consumption and smoking prevalence, designing policies that minimise the economic impact on retailers would be a win-win solution for all parties involved. This further emphasises the need for more ”retailer-friendly” policies in equitably reducing tobacco sales while maintaining retailer sustainability, such as business diversification into non-tobacco-related products [5, 89].

In addition, we found that simulations with dynamic retail pricing could serve as a valuable reference when considering the competitive factors among retailers. The simulations delivered a slightly more severe impact on the number of retailers and produced a more significant result on smoking consumption and smoking prevalence. When designing a new licencing policy scheme, policymakers must also consider the behavioral tendencies of retailers, as their increased competitiveness can lead to more detrimental financial impacts in aggregate.

We identified several limitations in the developed model. First, we implemented a simple cessation mechanism in the model, as described in Section 3.4.3. In reality, the cessation mechanism is much more complex and can involve social contagion as a key driver [44]. While agent-based modeling (ABM) is well-suited for implementing such smoking dynamics, we opted for a simplified cessation scheme to avoid complicating the model. However, implementing a network structure within the cessation scheme would make the model more representative of real-world situations. Additionally, although we incorporated retailer responses to represent the dynamic nature of the tobacco retail environment, the behavior embedded in the model remains relatively simple. In reality, there is potential for implementing more complex or advanced behaviors. For example, retailers could employ strategies based on game theory, considering the conditions of nearby retailers. If retailers recognise that many surrounding retailers have stopped selling tobacco, they might decide to pay the licence fee and resume selling tobacco.

Chapter 6

Conclusions and Future Work

The progressive licence fees scheme can serve as a strategic policy instrument that can be flexibly adjusted to reduce the availability of tobacco retailers in accordance with predetermined objectives. However, its implementation will heavily depend on the fee structure used, the size of the initial base fee, the level of annual increment, the geographical location of the retailers, and the potential price competition among them. Policymakers' awareness of the spatial impacts of such policies is crucial for the effective design of new licensing policies in the future. Additionally, it is important to note that reducing retailer density through license fee policies does not automatically lead to significant changes in consumption patterns or reductions in smoking prevalence. Moving forward, policymakers must formulate a more sustainable reduction scheme that considers the overall continuity of retailers' businesses, supported by a holistic approach that addresses both supply and demand aspects.

We identified several potential developments that could be made to the existing model. First, future works could implement a more complex cessation scheme by integrating network structure to simulate social contagion. This would provide a more accurate depiction of the impact on smoking prevalence compared to the simple cessation model currently used. Moreover, future works could also assess the impact of implementing a policy mix combining several fee structures into one policy package with different levels of initial fees. Using a combination of different fee schemes is considered an effective approach for equitably reducing retailer density across different geographical areas, as recommended by [5]. By conducting this simulation, policymakers can gain additional insights into the effectiveness of implementing this policy in the future compared to current fee schemes.

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Appendix A

Supplementary Materials

A.1 Environment Statistics

Table A.1: Environment Statistics

Parameter	Urban	Rural	Least-Deprived	Most-Deprived	Notes
Data zone area	0.478	12.243	10.858	1.863	per km^2
Grid Size	25	127	117	51	10 per km^2
Total Population	782.914	760.636	800.508	743.042	per data zone
Adult Proportion	0.2	0.2	0.2	0.2	
Retailer density					
Large retailer	0.206	0.002	0.036	0.244	per km^2
Small retailer	3.571	0.277	0.391	3.483	per km^2
Workplace density	32.37	0.79	6.58	16.58	per km^2
House density	362.55	350.22	345.13	367.64	per data zone
Transport mode proportion					
Car	0.645	0.645	0.708	0.582	
Public transport	0.120	0.120	0.077	0.164	
Other	0.234	0.234	0.213	0.254	
Transport speed					
Car	38.78	38.78	38.78	38.78	kph
Public transport	15	15	15	15	kph
Other	2.1	2.1	2.1	2.1	kph
Prevalence	0.16	0.12	0.07	0.25	

Retailer density for urban and rural areas was calculated using weight parameters (see Appendix A.10) from the following data:

Table A.2: Data used for retailer density in urban area

Retailer Type	**Urban Most-deprived**	**Urban Least-deprived**
Urban, Weight: [0.556, 0.444]		
Off-licence	0.55646	0.05426
Newsagent	0.34361	0.06837
Other	0.46524	0.04558
Petrol station	0.27975	0.09441
Pub/club	0.50173	0.09007
Private home	0.03648	0.03038
Small retailer	3.51822	0.32991

Table A.3: Data used for retailer density in rural area

Retailer Type	**Rural Most-deprived**	**Rural Least-deprived**
Rural, Weight: [0.250, 0.750]		
Off-licence	0.03745	0.00140
Newsagent	0.0	0.00420
Other	0.01872	0.00093
Petrol station	0.03121	0.00373
Pub/club	0.02496	0.00420
Private home	0.00624	0.00186
Small retailer	0.33706	0.01213

Table A.4: Data used for retailer density in least-deprived area

Retailer Type	**Urban Least-deprived**	**Rural Least-deprived**
Rural, Weight: [0.971, 0.029]		
Off-licence	0.05426	0.00140
Newsagent	0.06837	0.00420
Other	0.04558	0.00093
Petrol station	0.09441	0.00373
Pub/club	0.09007	0.00420
Private home	0.03038	0.00186
Small retailer	0.32991	0.01213

Table A.5: Data used for retailer density in most-deprived area

Retailer Type	Urban Most-deprived	Rural Most-deprived
Rural, Weight: [0.939, 0.061]		
Off-licence	0.55646	0.03745
Newsagent	0.34361	0.00000
Other	0.46524	0.01872
Petrol station	0.27975	0.03121
Pub/club	0.50173	0.02496
Private home	0.03648	0.00624
Small retailer	3.51822	0.33706

We used data based on SIMD quintiles from the Scottish National Health Survey 2022 for smoking prevalence. We selected data from the first and last quintiles for the most-deprived and least-deprived areas, respectively. For urban and rural areas, we calculated the values using the weight parameters obtained as detailed in Appendix 1. This was done to avoid bias in the population proportions used, as in the calculation of weight parameters, we based the calculations on the first and last two deciles to determine the total proportion of the population living in least-deprived and most-deprived areas.

A.2 Retailer Statistics

Table A.6: Retailer Statistics

Parameter	Urban	Rural	Least-Deprived	Most-Deprived	Notes
Price pack	[10.615, 0.0381, 8.45, 15.79]	[11.0543, 0.0541, 8.95, 16.82]	[10.83465, 0.0461, 8.7, 16.305]	[10.83465, 0.0461, 8.7, 16.305]	[mean, sd, min, max]
Cost per pack	[10.615, 0.0381, 8.45, 15.79]	[11.0543, 0.0541, 8.95, 16.82]	[10.83465, 0.0461, 8.7, 16.305]	[10.83465, 0.0461, 8.7, 16.305]	[mean, sd, min, max]

We used the weight parameters (Appendix A.10 to calculate the price pack and cost per pack for four areas (urban. rural. least-deprived, and most-deprived).

A.3 Policy scenarios

Table A.7: Policy Test Scenarios

Policy	**Policy settings**		**Area Type**	**Repetitions**	**Total runs**
	Fee Structure	**Annual Increment**			
Baseline	n/a	n/a	All	100	400
Universal-low	Universal	20%	All	100	400
Universal-high	Universal	50%	All	100	400
Volumetric-low	Volumetric	20%	All	100	400
Volumetric-high	Volumetric	50%	All	100	400
Rural/Urban-low	Rural/urban	20%	Urban, rural	100	200
Rural/Urban-high	Rural/urban	50%	Urban, rural	100	200
Universal-low 2*	Universal	20%	Urban	100	100
Universal-high 2*	Universal	50%	Urban	100	100
Volumetric-low 2*	Universal	20%	Urban	100	100
Volumetric-high 2*	Universal	50%	Urban	100	100
Total					**2800**

* Simulation with retail pricing dynamics where retailers dynamically update their pack price based on the average weighted neighbor prices

A.4 Retailers Proximity Network Formation

Let E be the set of edges in the network, d be the Manhattan distance function, and θ be the distance threshold.

$$E = \{(u,v) \mid u,v \in N \text{ and } d(\text{location}(u),\text{location}(v)) < \theta\}$$

where u and v are retailers in the set N, representing all retailers in the network, and $d(\text{location}(u),\text{location}(v))$ is the Manhattan distance between the locations of retailers u and v:

$$d((x_1,y_1),(x_2,y_2)) = |x_1 - x_2| + |y_1 - y_2| \tag{A.1}$$

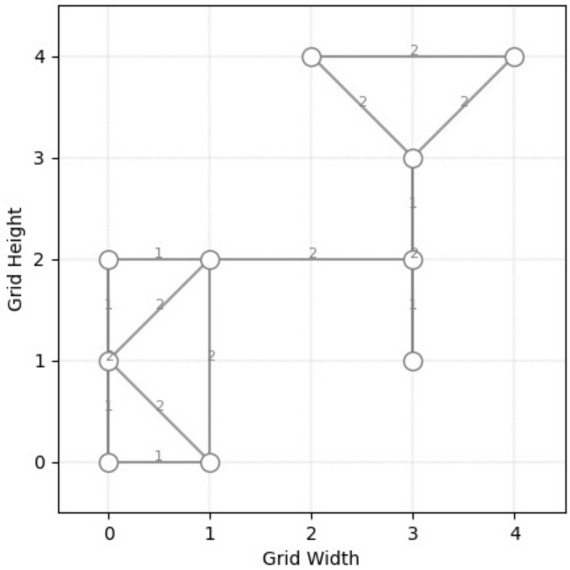

Figure A.1: Example of a retailers network generated during model initialisation for a 5x5 grid with 10 retailers and a distance threshold of 3.

A.5 Trembling Hand Mechanisme

With a high probability $(1-\varepsilon)$, the agent selects the retailer with the lowest total cost (C_r). To reflect occasional irrational choices, with a small probability (ε), set to 0.025, the agent may choose a different retailer. The probability of selecting any other retailer is based on their rank in terms of the total cost, using the formula:

$$\text{Prob}_{\text{retailer}} = (1-x)^{\text{rank(retailer)}-1} \times x \tag{A.2}$$

where rank(retailer) is the ascending rank of the retailer's total cost and x is set to 0.5. This method ensures that while the lowest-cost option is usually chosen, there is a stochastic variation that better simulates human behavior.

A.6 Price Elasticity

The price elasticity coefficients used in the model are specific to each Scottish Index of Multiple Deprivation (SIMD) quintile. The values are as follows: SIMD1 (most deprived) is -1.35, SIMD2 is -1.28, SIMD3 is -1.21, SIMD4 is -1.14, and SIMD5 (least deprived) is -1.07.

To calculate the urban price elasticity based on the SIMD data we use a weighted average of the price elasticity coefficients. Given that urban areas tend to have higher levels of deprivation [90], we place more weight on the more deprived SIMD quintiles. The weights used are $[0.6, 0.0, 0.0, 0.0, 0.4]$, corresponding to the proportion of the population in each SIMD quintile:

$$\varepsilon_{\text{urban}} = \sum_{i=1}^{5} \text{SIMD}_i \times w_{\text{urban},i}$$

For rural areas, a different set of weights $[0.3, 0.0, 0.0, 0.0, 0.703]$ is used to reflect the distribution of deprivation levels:

$$\varepsilon_{\text{rural}} = \sum_{i=1}^{5} \text{SIMD}_i \times w_{\text{rural},i}$$

For the least-deprived areas, the elasticity is taken directly from the SIMD5 coefficient:

$$\varepsilon_{\text{least-deprived}} = \text{SIMD}_5$$

For the most-deprived areas, the elasticity is taken directly from the SIMD1 coefficient:

$$\varepsilon_{\text{most-deprived}} = \text{SIMD}_1$$

A.7 Previous Age Agent

The Previous Age Agent class ensures the continuous influx of new agents into the target age group (35-44) within the simulation model. This mechanism simulates the aging process and the introduction of new agents, providing a dynamic and realistic population flow. The class initialises each agent with an age parameter and calculates the agent's age in years. These agents are added to the model's schedule but have not yet been placed on the grid. Each day, the agent's age is incremented by one, and every 30 simulation steps (representing approximately one month), the Previous Age Agent's age in years is recalculated.

When an Adult Agent reaches the age of 45, they are removed from the current schedule. Concurrently, Previous Age Agents who turn 35 are transformed into new Adult Agents. This transformation involves updating their status and integrating them into the model as active participants within the 35-44 age range.

A.8 Interactions between Agents and Environment

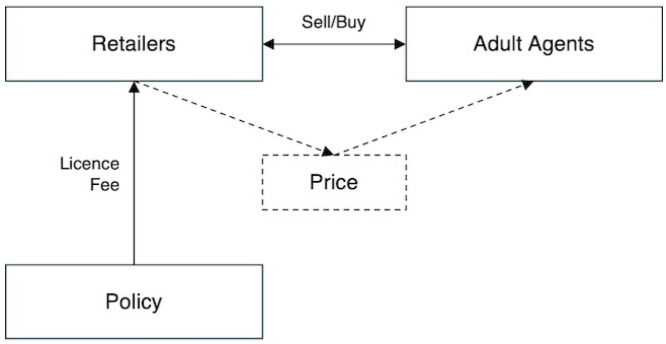

Figure A.2: Diagram illustrating the direct and indirect interactions between agents and environment in the simulation model.

A.9 Buy Cigarettes Algorithm

Algorithm 1 Buy cigarettes algorithm

```
function BUY_CIGARETTES
    packs_to_buy ← CALCULATE_PACKS_TO_BUY
    if packs_to_buy > 0 then
        total_cost ← (packs_to_buy × favorite_retailer.pack_price) + trip_cost
        if money > total_cost then
            cigarette_inventory ← cigarette_inventory + (packs_to_buy × 20)
            money ← money - total_cost
            FAVORITE_RETAILER.SELL_CIGARETTES(packs_to_buy)
        end if
    else
        return
    end if
end function
```

Algorithm 2 Calculate packs to buy algorithm

```
function CALCULATE_PACKS_TO_BUY(self)
    number_packs_wanted ← RANDINT(daily_cigarette_consumption / 20, 10)
    money_after_cost ← self.money - self.trip_cost
    number_packs_affordable ← money_after_cost // favorite_retailer.pack_price
    number_packs_to_buy ← MIN(number_packs_wanted, number_packs_affordable)
    return number_of_packs_to_buy
end function
```

A.10 Weight Parameters Calculation

Table A.8: Total Population and Deprivation Percentages

Area	Total Population[1]	Least-deprived	Most-deprived
Remote Rural (RR)	299115	0.031	0.027
Accessible Rural (AR)	660901	0.04	012
Other Urban Areas (OUA)	1843792	0.217	0.194
Large Urban Areas (LUA)	2061049	0.271	0.27

[1] Based on Scotland's Census 2022

We used empirical data from the Scottish Government's Report [82] to calculate the weight parameters. First, we classified remote rural and accessible rural into rural areas, while other urban areas and large urban areas were classified as urban areas. Since the report only included the first 5 SIMD deciles for each area, we generated the last 5 deciles based on [91, 92] (Figure A.3). We then calculated the percentage of the population living in the most-deprived and least-deprived areas based on the first two and last two SIMD deciles across the four areas (detailed calculations are presented in Table A.8).

By combining census data for each of these four areas, we then calculated the total population based on the previously determined percentages of least-deprived and most-deprived areas. Finally, we calculated the proportion of the total population in each area type to determine the weight parameters for the model (Table A.9, A.10, and A.11). Next, we performed a calibration of 2-5% for each area to achieve consistent results across all areas. The calibration results, as shown in Table 4.1, were subsequently used as weight parameters in the model.

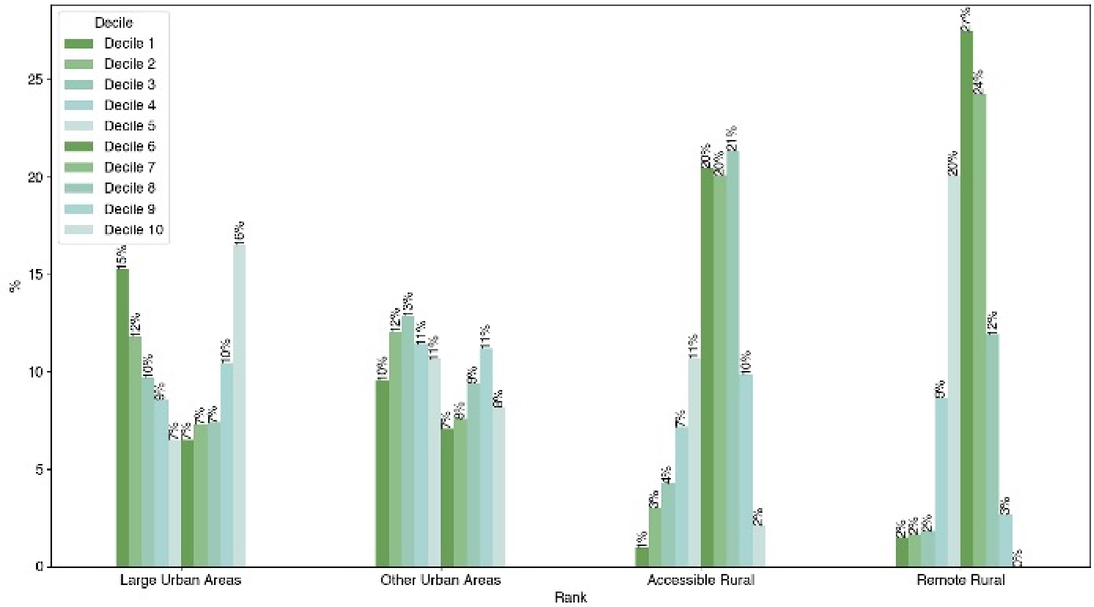

Figure A.3: Population by SIMD deciles and six-fold urban/rural classification.

Table A.9: Total Population and Weight Parameters for Least-deprived and Most-deprived Areas

Area Type	**Rural**		**Urban**	
	RR	**AR**	**OUA**	**LUA**
Least-deprived	8076.105	79308.12	357695.648	556483.23
Total/Proportion	87384.225 **(0.087247848)**		914178.878 **(0,912752152)**	
Most-deprived	9272.565	26436.04	400102.864	558544.279
Total/Proportion	35708.605 **(0.035911297)**		958647.143 **(0.964088703)**	

Table A.10: Total Population and Weight Parameters for Urban Areas

Area Type	**Least-deprived**		**Most-deprived**	
	OUA	**LUA**	**OUA**	**LUA**
Urban	357695.648	556483.23	400102.864	558544.279
Total/Proportion	914178.878 **(0.488128031)**		958647.143 **(0.511871969)**	

Table A.11: Total Population and Weight Parameters for Urban Areas

Area Type	Least-deprived		Most-deprived	
	RR	**AR**	**RR**	**AR**
Rural	8076.105	79308.12	9272.565	26436.04
Total/Proportion	87384.225 (**0.709905077**)		35708.605 (**0.290094923**)	

A.11 Output Validation

Table A.12: Output Validation

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Model's Output				
Grid size	35 x 35	207 x 207	57 x 57	35 x 35
Retailers	S: 48 L: 3	S: 65 L: 1	S: 24 L: 2	S: 74 L: 4
Avg. sales volume	34,366.52	19,318.44	26,892.47	38,298.18
Avg. gross profit	1,468.41	791.11	1,202.90	1,583.35
Avg. total sales	1,752,692.86	1,275,017.06	699,204.46	2,987,258.80
Avg. smoking rates	12.16	11.83	10.94	13.46
Prevalence	0.160	0.119	0.070	0.249
Avg. pack price	10.98	11.2	11.13	10.83
Historical Data (2022)				
Avg. sales volume	45,399.97	26,192.08	36,768.34	50,905.51
Avg. gross profit	1,978.17	1,078,89	1,685.40	2,111.04

A.12 Baseline Model Sensitivity Analysis

Table A.13: Parameters in sensitivity analysis

Parameter	Value Range	Base Value
Total Population	[10000, 15000, 20000, 25000, 30000]	20000
Weight Parameters	[0.5, 0.5] for all area types	Urban: [0.6, 0.4], Rural: [0.3, 0.7], Least-deprived: [0.35, 0.65], Most-deprived: [0.87, 0.13]
Trembling Hand Epsilon	[0.005, 0.05]	0.025

Total Population

The overall population parameter has a significant impact on several other parameters within the model. It determines the number of adult agents and smokers, the grid size, and the number of retailers to be simulated. The grid size is calculated based on the proportion of the total population compared to the average population in the data zones. Meanwhile, the number of retailers depends on the grid size, which is determined by the retailer density parameter for each area type.

Table A.14: Sensitivity Analysis Observations (Total Populations

Parameter	Mean	Std	Min	Max	IQR
Total Population: 10000					
Avg. Sales	34706.44	2466.17	28992.0	41160.27	3296.27
Avg. Gross Profit	1490.28	199.86	1126.96	2001.0	283.65
Prevalence	0.16	0.01	0.13	0.19	0.01
Total Population: 15000					
Avg. Sales	35323.68	2231.22	30309.01	41238.74	3464.1
Avg. Gross Profit	1542.26	168.2	1005.67	1902.75	209.79
Prevalence	0.16	0.01	0.14	0.18	0.01
Total Population: 20000 (base value)					
Avg. Sales	34405.44	1616.47	30768.37	39152.16	2243.04
Avg. Gross Profit	1451.16	168.97	1123.83	1891.93	225.55
Prevalence	0.16	0.01	0.15	0.18	0.01
Total Population: 25000					
Avg. Sales	35205.64	1583.18	32132.26	39026.13	2417.85
Avg. Gross Profit	1531.53	174.54	1148.6	1920.31	226.3
Prevalence	0.16	0.01	0.15	0.18	0.01
Total Population: 30000					
Avg. Sales	35903.34	1460.6	31982.19	39557.99	1679.18
Avg. Gross Profit	1563.54	162.64	1235.52	1930.11	234.17
Prevalence	0.16	0.01	0.15	0.18	0.01
All Combined					
Avg. Sales	35108.91	1975.47	28992.0	41238.74	2707.01
Avg. Gross Profit	1515.75	179.19	1005.67	2001.0	242.87
Prevalence	0.16	0.01	0.13	0.19	0.01

The simulation results indicate the average sales and gross profit values for various total population parameter settings. Overall, the model produced stable average sales (gross profit) values around 35,000 (1,500) with a standard deviation of 2,000 (180). The low interquartile range, covering the spread of 50% of the values, demonstrates that variations in the total population parameter do not significantly affect the model output. The lowest average sales value, around 29,000, occurred when the model generated a relatively low prevalence value of 0.13. At the same time, the highest value, around 41,000, occurred when the model generated a higher prevalence value of 0.18-0.19. Overall, with stable average sales and a low interquartile range, we find that our model is quite robust with respect to the total population parameter.

Trembling Hand Coefficient

Table A.15: Sensitivity Analysis Observations (Trembling Hand

Parameter	Mean	Std	Min	Max	IQR
Trembling Hand Coefficient: 0.001					
Avg. Sales	34151.74	1563.99	30484.84	37798.82	2140.23
Avg. Gross Profit	1460.45	156.87	1059.57	2057.53	198.52
Prevalence	0.16	0.01	0.15	0.17	0.01
Trip Cost	1.35	0.03	1.27	1.44	0.04
Trembling Hand Coefficient: 0.005					
Avg. Sales	34295.07	1763.27	30130.85	37894.9	2338.86
Avg. Gross Profit	1487.45	163.13	1179.63	1960.1	197.88
Prevalence	0.16	0.01	0.14	0.18	0.01
Trip Cost	1.36	0.04	1.23	1.48	0.06
Trembling Hand Coefficient: 0.01					
Avg. Sales	34306.2	1842.44	30471.5	38145.23	2408.43
Avg. Gross Profit	1473.32	171.37	1139.82	1919.55	223.31
Prevalence	0.16	0.01	0.14	0.18	0.01
Trip Cost	1.35	0.04	1.26	1.44	0.06
Trembling Hand Coefficient: 0.025					
Avg. Sales	34405.44	1616.47	30768.37	39152.16	2243.04
Avg. Gross Profit	1451.16	168.97	1123.83	1891.93	225.55
Prevalence	0.16	0.01	0.15	0.18	0.01
Trip Cost	1.36	0.05	1.25	1.5	0.05
Trembling Hand Coefficient: 0.05					
Avg. Sales	34008.15	1613.77	29942.61	37598.95	2349.74
Avg. Gross Profit	1462.72	162.37	1154.89	2206.49	214.39
Prevalence	0.16	0.01	0.14	0.17	0.01
Trip Cost	1.37	0.05	1.27	1.5	0.06
Trembling Hand Coefficient: 0.075					

Continued on next page

Table A.15 – *Sensitivity Analysis (continued)*

Parameter	**Mean**	**Std**	**Min**	**Max**	**IQR**
Avg. Sales	34704.27	1732.52	30658.69	40580.52	1933.04
Avg. Gross Profit	1496.6	163.96	1117.92	2033.39	208.62
Prevalence	0.16	0.01	0.15	0.18	0.01
Trip Cost	1.37	0.05	1.26	1.48	0.06
Trembling Hand Coefficient: 0.1					
Avg. Sales	34012.04	1795.5	29274.12	38040.26	2365.07
Avg. Gross Profit	1454.16	160.69	1149.55	1869.49	217.08
Prevalence	0.16	0.01	0.14	0.17	0.01
Trip Cost	1.39	0.05	1.29	1.51	0.07
Trembling Hand Coefficient: 0.3					
Avg. Sales	34481.46	1821.8	29957.78	40136.21	2585.52
Avg. Gross Profit	1462.3	135.08	1200.78	1920.96	197.57
Prevalence	0.16	0.01	0.14	0.18	0.01
Trip Cost	1.45	0.05	1.32	1.59	0.08
All Combined					
Avg. Sales	34295.55	1728.5	29274.12	40580.52	2395.07
Avg. Gross Profit	1468.52	160.65	1059.57	2206.49	222.75
Prevalence	0.16	0.01	0.14	0.18	0.01
Trip Cost	1.38	0.05	1.23	1.59	0.07

The trembling hand coefficient is a parameter used by adult agents when choosing their favorite retailers (Equation A.2). The larger the value of this parameter, the higher the probability that an agent will choose retailers with suboptimal costs when purchasing cigarettes. From the sensitivity analysis results (Table A.15), we observed that the average sales and gross profit for various values of the trembling hand coefficient remained relatively stable, around 34,000 and 1,400, respectively. The variation in the trembling hand coefficient did not significantly impact these two model outputs; however, it is important to note that this variable influences the trip costs of smokers. We observed a positive correlation between these two variables, with the change in trip costs being one order of magnitude smaller than the change in the trembling hand coefficient.

Weight Parameters

Table A.16: Sensitivity Analysis Observations (Weight Parameters)

Parameter	Sales Volume	Gross Profit	Sales Volume Hist.	Gross Profit Hist.
Base values				
Urban [0.556, 0.444]	34366.52 (↓ 25%)	1468.41 (↓ 26%)	45399.97	1978.17
Rural [0.250, 0.750]	19318.44 (↓ 26%)	791.11 (↓ 27%)	26192.08	1078,89
Least-deprived [0.971, 0.029]	26892.47 (↓ 27%)	1202.9 (↓ 29%)	36768.34	1685.40
Most-deprived [0.939, 0.0061]	38298.18 (↓ 25%)	1583.35 (↓ 25%)	50905.51	2111.04
Variations				
Urban [0.5, 0.5]	37162.22 (↓ 17%)	1625.44 (↓ 17%)	44571.97	1952.78
Rural [0.5, 0.5]	14123.23 (↓ 52%)	544.67 (↓ 53%)	28897.98	1162.60
Least-deprived [0.5, 0.5]	6011.52 (↓ 80%)	248.58 (↓ 81%)	30332.65	1336.22
Most-deprived [0.5, 0.5]	16326.06 (↓ 62%)	624.54 (↓ 64%)	43137.29	1725.09

As explained in Section 4.2, weight parameters are crucial in determining the proportions of various parameter values derived from the data provided[1]. Due to time constraints and the large parameter space, we did not conduct a detailed sensitivity analysis for this parameter. We made comparisons using only one variation: the simple average for all area types.

From the results, we found that the discrepancy in sales volume and gross profit increases with larger deviations in weight parameters. The smallest discrepancy was observed in urban areas, with differences of approximately 17% for sales volume and gross profit. This is because the weight parameter proportions do not deviate significantly from the base value of [0.556, 0.444]. Conversely, a significant discrepancy was observed in the least-deprived areas, where sales volume and gross profit were approximately 80% lower compared to the base value. This substantial difference is due

[1] These weight parameters influence the values for smoking prevalence, grid dimensions, retailer density, workplace density, housing density, transport mode proportions, pack price distribution, profit per stick distribution, and wage distribution.

to the weight parameters deviating significantly from the base value [0.971, 0.0029].

The results suggest that weight parameters have a substantial impact on both sales volume and gross profit. These parameters determine the number of retailers to be simulated, directly affecting average sales volume and gross profit calculation. Therefore, weight parameters must be selected carefully. As explained in Section 4.2, choosing weight parameters based on simple averages caused the model output to deviate significantly from historical data. We refined this assumption by calculating weight parameters based on empirical data proportions of the population (using population estimates by the 6-fold Urban Rural Classification and SIMD deciles). Detailed calculations are presented in Appendix A.10.

A.13 Base Fees for Simulations

For the universal fee, we used a base fee equivalent to 30% of the median gross profit of all retailers across the four areas in the baseline model. For the volumetric fee, we used a base fee of 30% of the median gross profit per 1000 sticks. For the urban/rural fee, the 30% calculation is based on the median for each urban and rural area. One thing to note is that these values represent only the proportion of profits generated by the 35-44 age group.

Table A.17: Base Fees

Area Type	Value	Notes
Universal	87.92 GBP	30% from all retailers in baseline model
Volumetric	12.05 GBP per 1000 sticks	30% from all retailers in baseline model
Urban/rural	Urban: 96.87 GBP Rural: 74.81 GBP	30% from retailers in urban and rural areas in baseline model

A.14 Simulation Result: Number of Retailers (%)

Table A.18: Average Number of Retailers (Percentage)

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Universal (0.2)				
Year 1	68.78	66.11	81.12	63.79
Year 2	65.82 (-4.30%)	63.68 (-3.67%)	78.69 (-2.99%)	61.73 (-3.22%)

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Table A.18 – *Average Number of Retailers (Percentage) (continued)*

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Year 3	63.69 (-7.42%)	60.79 (-8.04%)	76.54 (-5.64%)	58.96 (-7.57%)
Year 4	60.75 (-11.68%)	57.56 (-12.92%)	74.46 (-8.23%)	56.55 (-11.35%)
Year 5	58.53 (-14.89%)	54.59 (-17.42%)	72.31 (-10.87%)	54.18 (-15.06%)
Universal (0.5)				
Year 1	69.14	66.71	81.04	63.99
Year 2	65.04 (-5.94%)	62.09 (-6.93%)	77.38 (-4.51%)	60.03 (-6.19%)
Year 3	60.96 (-11.85%)	56.32 (-15.57%)	72.96 (-9.98%)	55.4 (-13.43%)
Year 4	55.39 (-19.85%)	49.09 (-26.42%)	66.77 (-17.61%)	49.78 (-22.22%)
Year 5	48.39 (-30.01%)	41.62 (-37.60%)	59.88 (-26.12%)	44.29 (-30.78%)
Volumetric (0.2)				
Year 1	100.0	100.0	100.0	100.0
Year 2	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)
Year 3	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)
Year 4	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)
Year 5	99.88 (-0.12%)	99.77 (-0.23%)	100.0 (0.00%)	98.36 (-1.64%)
Volumetric (0.5)				
Year 1	100.0	100.0	100.0	100.0
Year 2	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)	100.0 (0.00%)
Year 3	97.92 (-2.08%)	97.76 (-2.24%)	100.0 (0.00%)	95.67 (-4.33%)
Year 4	71.98 (-28.02%)	72.36 (-27.64%)	77.19 (-22.81%)	69.59 (-30.41%)
Year 5	32.75 (-67.25%)	31.26 (-68.74%)	41.38 (-58.62%)	27.96 (-72.04%)
Urban/Rural (0.2)				
Year 1	67.86	67.88	-	-
Year 2	65.29 (-3.79%)	65.21 (-3.93%)	-	-
Year 3	62.45 (-7.96%)	62.61 (-7.77%)	-	-
Year 4	60.12 (-11.39%)	59.98 (-11.63%)	-	-
Year 5	57.51 (-15.23%)	57.03 (-15.99%)	-	-
Urban/Rural (0.5)				
Year 1	67.79	67.38	-	-
Year 2	63.87 (-5.78%)	64.0 (-5.01%)	-	-
Year 3	58.62 (-13.51%)	58.52 (-13.15%)	-	-
Year 4	53.44 (-21.18%)	52.17 (-22.55%)	-	-
Year 5	47.03 (-30.63%)	44.86 (-33.44%)	-	-

A.15 Simulation Result: Median Gross Profits

Table A.19: Median Gross Profit among Retailers

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Baseline				
Year 1	306.3	251.3	518.7	166.9
Universal (20%)				
Year 1	234.78	170.6	429.57	159.16
Year 2	631.12 (+168.8%)	430.28 (+152.2%)	630.23 (+46.7%)	574.1 (+260.7%)
Year 3	694.71 (+196.0%)	447.46 (+162.3%)	674.96 (+57.1%)	614.29 (+285.9%)
Year 4	723.0 (+207.9%)	466.9 (+173.7%)	708.4 (+64.9%)	690.59 (+333.8%)
Year 5	789.01 (+236.0%)	497.16 (+191.4%)	723.02 (+68.4%)	740.59 (+365.3%)
Universal (50%)				
Year 1	231.12	166.76	444.88	159.85
Year 2	608.05 (+163.0%)	395.64 (+137.3%)	639.19 (+43.7%)	574.44 (+259.3%)
Year 3	640.53 (+177.1%)	402.05 (+141.0%)	664.21 (+49.4%)	612.1 (+283.0%)
Year 4	660.83 (+185.9%)	409.38 (+145.5%)	642.84 (+44.5%)	674.97 (+322.2%)
Year 5	723.37 (+213.0%)	433.84 (+160.1%)	650.96 (+46.3%)	751.29 (+370.1%)
Volumetric (20%)				
Year 1	234.28	174.65	381.01	166.99
Year 2	210.31 (-10.2%)	153.36 (-12.2%)	338.9 (-11.0%)	151.7 (-9.2%)
Year 3	182.71 (-22.0%)	129.92 (-25.6%)	304.29 (-20.1%)	133.52 (-20.0%)
Year 4	151.06 (-35.5%)	103.02 (-41.0%)	262.6 (-31.1%)	104.89 (-37.2%)
Year 5	105.8 (-54.9%)	67.82 (-61.2%)	193.83 (-49.1%)	70.26 (-57.9%)
Volumetric (50%)				
Year 1	212.0	172.78	384.38	162.55
Year 2	165.42 (-22.0%)	128.01 (-25.9%)	305.7 (-20.5%)	122.17 (-24.8%)
Year 3	76.2 (-64.1%)	51.18 (-70.4%)	168.06 (-56.3%)	43.25 (-73.4%)
Year 4	2.68 (-98.7%)	1.39 (-99.2%)	22.82 (-94.1%)	0.0 (-100.0%)
Year 5	-19.3 (-109.1%)	-9.06 (-105.2%)	-4.52 (-101.2%)	-32.66 (-120.1%)
Urban/Rural (20%)				
Year 1	205.67	183.68	-	-
Year 2	625.12 (+204.0%)	431.06 (+134.7%)	-	-
Year 3	674.68 (+228.1%)	464.66 (+152.9%)	-	-
Year 4	739.82 (+259.7%)	476.98 (+159.7%)	-	-
Year 5	796.34 (+287.3%)	496.71 (+170.6%)	-	-
Urban/Rural (50%)				
Year 1	214.7	180.47	-	-
Year 2	593.05 (+176.2%)	424.63 (+135.3%)	-	-

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Table A.19 – *Median Gross Profits (continued)*

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Year 3	656.18 (+205.5%)	431.32 (+138.9%)	-	-
Year 4	734.8 (+242.3%)	430.8 (+138.7%)	-	-
Year 5	789.2 (+267.6%)	446.84 (+147.6%)	-	-

A.16 Simulation Result: Trip Costs for Buying Cigarettes

Table A.20: Trip Costs for Buying Cigarettes

Parameter	Urban	Rural	Least-Deprived	Most-Deprived
Universal (0.2)				
Year 1	1.354	1.790	1.711	1.247
Year 3	1.378 (+1.77%)	1.885 (+5.31%)	1.770 (+3.44%)	1.262 (+1.20%)
Year 5	1.401 (+3.47%)	2.000 (+11.73%)	1.826 (+6.72%)	1.276 (+2.32%)
Universal (0.5)				
Year 1	1.364	1.787	1.703	1.249
Year 3	1.396 (+2.35%)	1.896 (+6.11%)	1.750 (+2.76%)	1.264 (+1.20%)
Year 5	1.435 (+5.20%)	2.144 (+20.01%)	1.855 (+8.93%)	1.296 (+3.76%)
Volumetric (0.2)				
Year 1	1.360	1.741	1.728	1.242
Year 3	1.365 (+0.37%)	1.784 (+2.47%)	1.751 (+1.33%)	1.244 (+0.16%)
Year 5	1.368 (+0.59%)	1.843 (+5.86%)	1.781 (+3.07%)	1.246 (+0.32%)
Volumetric (0.5)				
Year 1	1.365	1.790	1.710	1.245
Year 3	1.373 (+0.59%)	1.807 (+0.95%)	1.736 (+1.52%)	1.249 (+0.32%)
Year 5	1.500 (+9.99%)	2.193 (+22.54%)	1.991 (+16.41%)	1.343 (+7.90%)
Urban/Rural (0.2)				
Year 1	1.356	1.785	-	-
Year 3	1.386 (+2.21%)	1.896 (+6.22%)	-	-
Year 5	1.409 (+3.91%)	1.996 (+11.81%)	-	-
Urban/Rural (0.5)				
Year 1	1.355	1.785	-	-
Year 3	1.386 (+2.29%)	1.910 (+7.00%)	-	-
Year 5	1.429 (+5.46%)	2.108 (+18.10%)	-	-

A.17 Simulation Result: Dynamic Retail Pricing

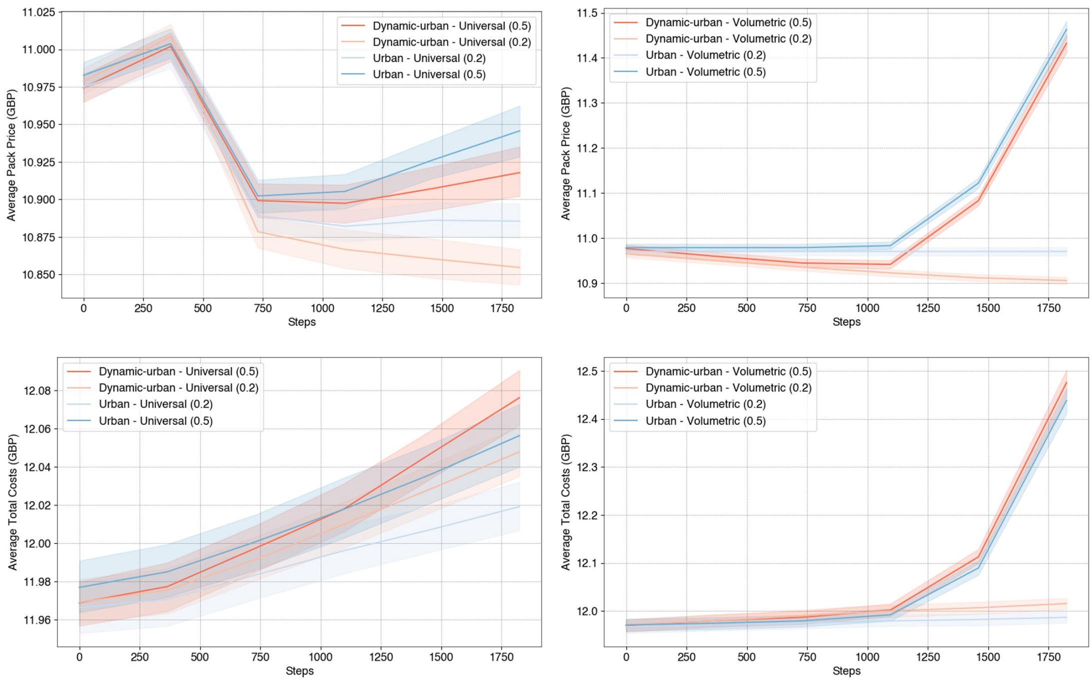

Figure A.4: Comparison of the pack prices and total costs in simulations with and without the dynamic retail pricing scheme for urban areas.

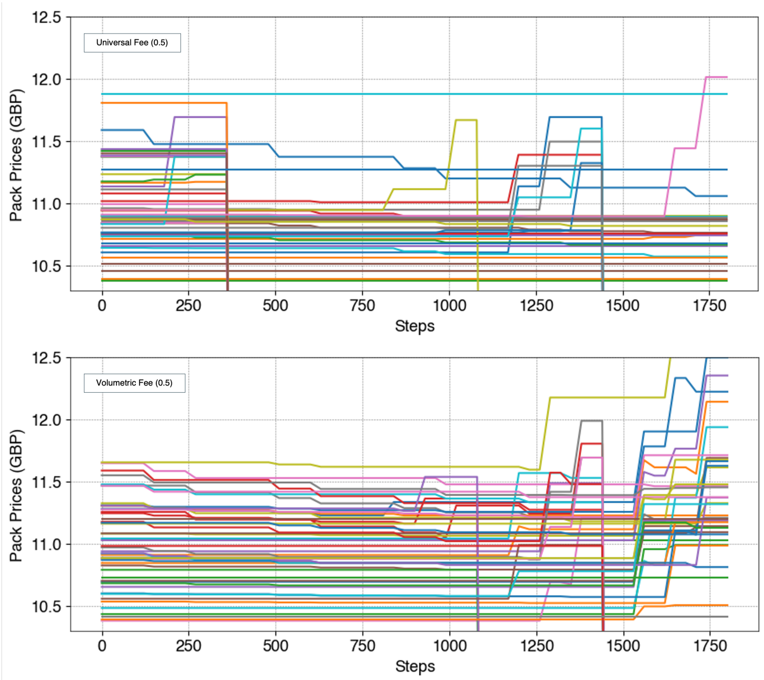

Figure A.5: Example of price pack per retailer for universal (left) and volumetric (right) fees taken from one sample iteration in dynamic retail pricing simulation.

Table A.21: Average smoking rates with dynamic retail pricing

Parameter	Year 1	Year 3	Year 5
Dynamic-urban			
Universal (0.2)	11.845	11.357 (-4.12%)	11.034 (-6.85%)
Universal (0.5)	11.91	11.421 (-4.11%)	11.275 (-5.34%)
Volumetric (0.2)	11.552	10.478 (-9.29%)	9.696 (-16.06%)
Volumetric (0.5)	11.541	10.372 (-10.12%)	8.355 (-27.64%)
Urban			
Universal (0.2)	12.152	12.116 (-0.30%)	12.133 (-0.16%)
Universal (0.5)	12.208	12.172 (-0.29%)	12.092 (-0.95%)
Volumetric (0.2)	12.229	12.241 (+0.10%)	12.229 (0.00%)
Volumetric (0.5)	12.346	12.218 (-1.04%)	10.482 (-15.10%)

A.18 Nonlinear Pattern on Volumetric Scheme

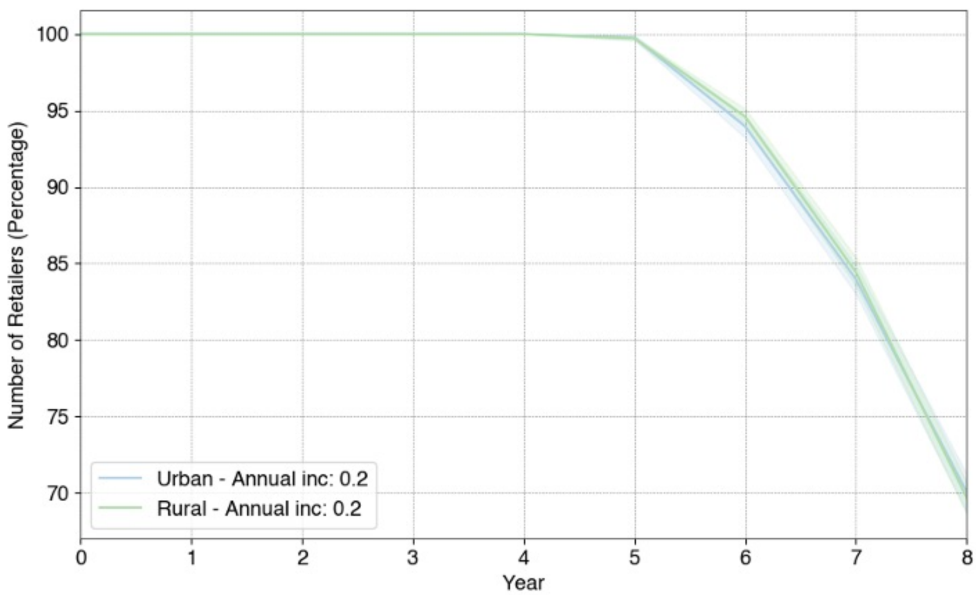

Figure A.6: Illustration of the nonlinear reduction effect in the volumetric scheme during the simulation in urban and rural areas with a 20% annual increment, extended over an eight-year horizon.