Agent-Based Models For Policy Making Evaluating the Impact of License Fee Policies on Retailer Behaviors

Peidi Li

Master of Science
School of Informatics
University of Edinburgh
2024

Abstract

This project investigates the impact of licence fee policies on retailer behaviors and smoking trends using the Agent-Based Modelling (ABM) approach. The model simulates interactions between various types of retailers—large chains, small independent stores, and noise retailers—and consumers in certain age groups within a virtual town, referencing principles of game theory to analyse pricing strategies and market exit decisions. By integrating real-world data, the model offers insights into how retailers respond to the financial pressures introduced by licence fees and the subsequent effects on market dynamics and public health outcomes. The results indicate that the introduction of a licence fee significantly reduces tobacco sales and gross profits, particularly in rural areas with lower retailer density, while also leading to a noticeable decrease in smoking rates among certain age groups. These findings provide valuable guidance for policymakers in designing effective tobacco control strategies, especially for the licence fee aspect, that leverage retailer reactions to reduce smoking prevalence.

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.

(*Peidi Li*)

Acknowledgements

First of all, I would like to express my gratitude to my supervisor, Dr. Valerio Restocchi, for his invaluable guidance and support throughout the entire process of this study. Your insightful feedback and expert advice have been very important in shaping the direction and outcomes of this study. The weekly meetings we held were not only critical in keeping the progress in the correct direction but also provided a platform for thoughtful discussions that may always deepen my understanding. Additionally, your responses to my countless emails ensured that I never felt unsupported during the process. Your encouragement and continuous support have always been a source of great motivation for me!

I would also like to extend my thanks to Dr. Roberto Valiente, whose work has provided not only additional data that significantly enriched my study but also provided precious advises for the model design.

Besides, I am particularly thankful to my teammates, Geri and Dharma, for their collaboration and intellectual exchange during different discussions on our research progress. Our communications were essential in keeping the project on track and motivating each other through the challenges we faced.

A special thanks to Hanwen, with whom I spent countless hours in the lab, working together despite we are working for different projects. Your partnership have been a crucial part for finishing this study.

Finally, I would like to thank my parents and my girlfriend for their unwavering support and encouragement throughout this journey. Your patience and understanding always allow me to persevere through the most challenging times.

Thank you all for your contributions to this work. Without your support, this thesis would not have been possible.

Table of Contents

Chapter 1

Introduction

1.1 Background

In recent years, tobacco usage management remains to be an urgent public health issue that has significant impacts on both social health and economic areas. According to the report of World Health Organisation (WHO), tobacco use causes more than 8 million deaths annually across countries, making smoking one of the leading causes of preventable disease and death[1]. In Scotland, despite the government has implemented various tobacco control policies since 2013, such as increased funding for tobacco control budgets, public smoking bans and related legal prohibitions[2], the smoking rate remains high in specific groups which are often at the peak of work and family pressures, where tobacco use may have long-term health implications on them.

To address the ongoing challenge of tobacco use, the Scottish government outlined multiple measures in 2018[2], aiming to reduce smoking rates to 5% lower by 2034. The introduction of tobacco retailer licence fees policy can be a critical role in the framework. The policy mandates that all stores must obtain a licence to continue their tobacco sales, which will lead to the increment of operational cost and the reduction of sales volume, thereby limiting the social accessibility of tobacco products[3]. The retailers' reaction is an indispensable part when researching the impact of the policy.

In this context, agent-based model(ABM) can be a crucial tool for understanding and predicting how tobacco retailers might respond to policy changes. ABM allows us to simulate the behaviours of different types of retailers and customers in a complex retail market environment, especially their choices under licence fee policy pressure. By modelling the decision-making processes of each agent, ABM captures micro-level dynamics that are often missed by traditional macroeconomic models[4]. Additionally, when simulating the strategies, the use of game theory can provide a method to analyse competitive and cooperative strategies among retailers, especially in pricing adjustments and market exit decisions[5].

1.2 Motivation

While the Scottish government has made some progress in reducing smoking rates, understanding the impact of introducing licence fees in certain areas is still a meaningful aspect when it comes to the actual behaviour of tobacco retailers. Particularly with the different types of retailers, such as large chains and small independent stores, may implement varying strategies to adapt to the policy to cope with the increasing cost.

Currently, existing research usually gives less attention to the responses of retailers. This kind of oversight may lead to misjudgments of policy effectiveness, especially in a complex market environment. Therefore, the motivation of this study is to fill this gap by employing ABM and game theory to simulate and analyse retailer strategy choices in various situations to observe the impact of licence fee policy.

1.3 Objectives

The primary goal of this project is to systematically analyse the strategy choices and market behaviours of tobacco retailers in a simulated environment in response to the licence fee policy using ABM and game theory. The objectives are listed as follow:

1. **Design a realistic model**: Construct an ABM that accurately simulates the real market to ensure the reliability of the project's findings.

2. **Design retailer strategy logic**: Implement the decision-making logic for retailers with Game Theory, simulating their pricing and market exit strategies.

3. **Analyse the impact on retailers**: Obtain the result from simulation and analyse the retailer reaction in several aspects (e.g. Profit & Sales Volume)

4. **Analyse the impact on smokers**: Obtain the result from simulation and analyse the agent situation in several aspects (e.g. Smoking Rate & Smoking Proportion)

The dissertation structure is listed as follows: Chapter 2 reviews relevant literature. Chapter 3 outlines methodologies. Chapter 4 covers implementation. Chapter 5 presents results and analysis. Chapter 6 conclusion with limitations and future works.

Chapter 2

Literature Review

2.1 Tobacco Retail

Tobacco retail is a crucial part of the whole supply chain, which will directly influence the accessibility of tobacco products. In recent years, researchers focus more on the impact of the tobacco retail environment, including how policy affects retailer behaviour and consumer habits.

Lee et al. (2022) evaluated New Zealand's tobacco retail reduction policy through simulation, demonstrating that reducing retail density can significantly decrease tobacco use among adults[6]. Also, the study by Combs et al. (2020) modeled the potential impact of certain policies in Tobacco Town demonstrated that policies could significantly affect the tobacco retail market[7]. Similarly, research by Robertson and Marsh (2019) found that reducing the number of retail outlets could effectively lower tobacco consumption[8].

Additionally, changes driven by tobacco tax policy may cause the pricing strategies of the whole tobacco business. For example, Gilmore et al. (2013) examined the tobacco market in UK and revealed how the tobacco industry adjusts pricing strategies in response to policies, sometimes undermining the effectiveness of such policies[9]. These market dynamics further reveal the importance of understanding retailers' strategic responses to licence fees for the successful implementation of policies.

Overall, research in the tobacco retail suggests that implementing licence fees policy and reducing the number of retailers can effectively reduce tobacco use among adult populations. These studies provide critical empirical support for model design.

2.2 Licence Fee

Licence fees have emerged as a powerful policy tool to regulate tobacco retail. By increasing the cost of doing business for tobacco retailers, these fees can potentially reduce the number of retail outlets and lead to decreased retail density[3]. In New South Wales (NSW), comprehensive measures combining licence, education, and enforcement have further denormalised tobacco smoking and significantly reduced smoking rates[10]. The framework for implementing licence systems has been explored worldwide. Various regions have experimented special authorisation to legally sell tobacco products, which is considered crucial for effective tobacco control and demoralising tobacco use[11].

Then, the effectiveness of licence fees may vary by region. In Scotland, Valiente et al. (2024) explored the geographical differences in the financial impacts of different forms of tobacco licence fees on small retailers[12]. Their study can provide a certain data for retailer agent part.

These findings highlight the importance of licence fees in tobacco retail, particularly in how they influence retail density and accessibility. Also, impacts caused by regional variations of these fees is essential for related policy making.

2.3 Game Theory

For the strategies of retailers, Game theory is an ideal approach to provides a robust framework for interactions analysis.

The application of game theory in retail settings helps illustrate how retailers adjust their strategies in response to the actions of competitors and other situations, which is crucial for understanding market dynamics and outcomes. For example, The study of Taylor et al. (2019) included game theory with Monte Carlo simulations to model retail marketing discount strategies[13], enabling more informed decisions in complex market environment. Similarly, research by Oxford Academic (2019) emphasises the role of game theory in pricing decisions among competitors[14], which is crucial in figuring out how a retailer should compete on price.

Furthermore, game theory plays a crucial role in analysing market exit strategies. Umbhauer (2022) examined market exit scenarios using the mini-max regret approach. This approach shows the possibility of game theory usage in market exits decisions.

In summary, game theory provides a powerful tool for the project to design the retailers' strategies from pricing strategies to market exit decisions. By leveraging game theory in retailer agents, more informed decisions can be made to simulate the real market environment.

2.4 Agent-Based Model

Agent-Based Model(ABM) has become an indispensable tool for analysing complex systems in tobacco retail environments. Different from traditional statistical methods, ABM simulates dynamic interactions between individual agents—such as retailers and consumers—and their environments, offering detailed insights into how these interactions change and related public health outcomes.

Feirman et al. (2017) demonstrated ABM's effectiveness in assessing tobacco control policies, showing how it captures the complex interactions between regulatory measures, retailer behaviour, and consumer choices[15], which provides a nuanced understanding of policy impacts that are often overlooked by traditional models. Similarly, Hammond (2015) emphasised ABM's role in designing targeted interventions, demonstrated its traits, advantages, and limitations[16]. In the study, the fast growing of ABM's application area in public health is confirmed, which certified its possibility in modelling tobacco retail market.

Another earlier study by Luke and Stamatakis (2012) discussed the value of systems science methods, including ABM, in public health research[17]. They highlighted ABM's ability to simulate how environments influence individual behaviours, which in turn affect broader outcomes. The Institute of Medicine (2015) further advocated for the broader application of ABM in tobacco regulation due to its capability to model adaptive systems where all factors can evolve continuously[18].

Moreover, Homer and Hirsch (2006) noted that ABM is particularly useful when traditional studies are not feasible[19]. They argued that ABM provides a detailed framework to evaluate long-term public health policies across different time-frames, making it an essential tool in tobacco control, where policies like retailer density regulations and pricing strategies have varied impacts across socioeconomic groups.

This research aims to bridge the gap in understanding the effects of licence fees on retailer strategies within the tobacco market by applying ABM and game theory. It will explore how policies influence competitive behaviours, such as pricing strategies and market exit decisions, among retailers. Additionally, the study will examine the implications of these strategic interactions on smokers behaviour, offering new insights into how regulatory policies shape both retailer decisions and public health outcomes.

Chapter 3

Methodology

3.1 Model Design

In this research, an Agent-Based Model(ABM) is designed to simulate interactions between retailers and consumers in a virtual town, aiming to assess the impacts of tobacco licence fee policies.

3.1.1 Structure

The development of the model was inspired by studies such as Combs et al. (2020), who demonstrated the powerful capabilities of ABM in tobacco retail area by modelling the tobacco town[7] and other similar approaches including the computational model designed by Luke et al.(2017)[20].

The main components of ABM include **Agents, Environment, Time Progression, Interactions Between Agents, and Data and Parameters**[21]. These components work together and form a dynamic system which is capable of simulating complex environment observed in the real world. In the following part, the main structure of ABM will be introduced according to these components.

As shown in Figure 3.1, the agent-based model environment has a basic structure like this figure 3.1.

For agents part, during the process, a detailed needs analysis is made to clarify the primary objective of our study, which is to assess the impact of licence fee policies, to observe retailer behaviour and market dynamics. Based on this analysis, we defined two main types of agents: Adult Agents and Retailer Agents, and established specific behaviour rules for each type. More detailed design for agents will be illustrated in the

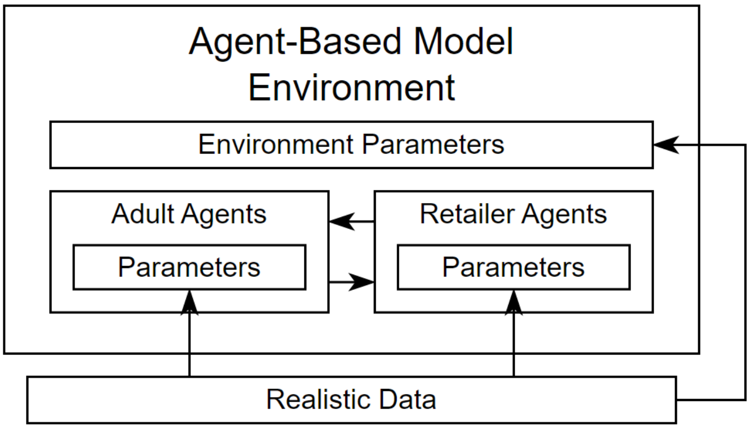

Figure 3.1: Basic Agent-Based Model Structure

related section in chapter3.2.

The environment in the model is a complex two-dimensional grid that represents the spatial layout of the virtual town. Each grid cell can represent a specific location, including residences, workspace areas, retailer store, etc., and the allocation of these areas can influence agent behaviour. For example, the smoker agents tend to go to the retailer store around which is nearer to his home or workplace. The environment also includes area types, transportation costs, and other factors that affect the agent behaviours. Agents not only move and interact within this environment but also adjust their strategies based on the geographical advantages or disadvantages.

Time progression uses a discrete time-step method in this study, with each time step representing one day in the real world. During each time step, all agents perform actions according to their behaviour rules. Random Scheduler is used to determine the order of agent actions, ensuring randomness and realism during the simulation.

Interactions between agents is a crucial part in the model, including both direct and indirect interactions formed through environment feedback. The direct interactions between Adult Agents and Retailer Agents mainly represent as tobacco purchasing behaviours, where consumers choose favourite retailers based on certain factors, while retailers attract consumers by adjusting prices or exit the market. Additionally, games among retailers is a key form of interaction, with price wars and market share battles. These interactions are driven by game theory strategies, where part of the retailers consider competitors' actions, market demand changes, and policy pressures when making decisions. Indirect interactions are reflected in how agent behaviours influence overall market dynamics. For instance, the exit of a major retailer might cause market price fluctuations, which in turn affect the other retailers and consumers.

The setting of data and parameters is the key to create a realistic simulation. The data sources for the model are extensive, including town status data, adult data, historical sales data, and more. These data are used to initialise the attributes of agents and environment, some of them are used for dynamically adjusting the model parameters during the simulation. For example, the price elasticity coefficient data is used for the update of the smoking rate of the agents. More detailed illustration of data and parameters will be explained in the following part.

3.1.2 Data

In this study, multiple data sources from both literature and official surveys is utilised to gather the necessary data for initialising model parameters and enabling model updates during simulation. These data basically comes from *Tobacco Control* journal literature[22, 23] etc. and government surveys[24, 25, 26, 27, 28], providing a solid foundation for more realistic modelling.

The environment data includes the characteristics of the town, as well as the necessary cost and coefficient for updating agent activities. The key data required are listed as follows:

- **Town Size**: Used for calculating dimensions which define the size of the town.
- **Total Population**: Used for calculating the number of adults.
- **Specific Age Group Proportion**: Used for calculating the number of adults aged 35-45, which is the main experiment subject.
- **Smoking Prevalence** : Used for calculating the number of smokers.
- **Households Count**: Used for generating the residences of the agents.
- **Business Density**: Used for generating the workplace of the agents.
- **Retailer Density**: Used for generating the retailers.
- **Transportation Costs**: Used for calculating costs for different transport mode.
- **Price Elasticity Coefficient**: Used for calculating the smoking rate changes.

Retailer data is critical for setting up agents and validate the model, mainly contains the price and sales data. The key data required are listed as follows:

- **Pack Price**: Used for generating initial pack price through statistics.
- **Cost Price**: Used for generating initial cost price through statistics.
- **Gross Profits**: Used for validating the gross profits calculated with data from various areas and crosscheck the authenticity.
- **Sales Volume** : Used for validating the sales volume calculated with data from various areas and crosscheck the authenticity.
- **Noise Retailer Proportion** : Used for calculating the number of noise traders.
- **Licence Fee**: Used for clarifying the licence fee calculate function.

The data for adult agents is basically about the wealth, smoking rate and transport mode. The key data required are listed as follows:

- **Wage Distribution**: Used for generating initial wage per week through Cumulative Distribution Function (CFD).
- **Spending Rate**: Used for calculating the spending rate on smoking among different SIMD groups.
- **Smoking Rate**: Used for calculating the consumption of cigarettes for each smoker.
- **Transport Mode Proportion** : Used for generating the transaction method for each adult agent, which consequently lead to different transport costs.

In summary, the data sources utilised are carefully selected to ensure the accuracy and realism of the ABM. By integrating diverse datasets from both academic literature and official surveys, the model can faithfully represent the complexities of the virtual town. The comprehensive data provides a robust foundation for ongoing updates and validation, ultimately enhancing the model's ability to simulate real-world scenarios.

3.1.3 Policy

The structure of the licence fee policy in this ABM is based on the relevant research methods in the recent study on the impact of licence fees caused by geographical differences[12]. Basically, the licence can be classified into different categories, including fixed fee for various regions, volumetric fee for unequal sales volume and others.

And for this project, a complex licence fee policy which combines both Urban-Rural component and Volumetric component is the most suitable way to apply to the model.

The Urban-Rural Component is determined by the geographical difference of urban and rural areas, aiming to reflect the operational cost differences between areas. Retailers in urban areas typically gain potentially higher profits for selling tobacco products. According to the equation in the study by Valiente[12]:

$$Y_{\text{urban}} = 76.37849x \quad \text{when} \quad x = 30 \quad \text{(i.e., potential fee level = 30\%)} \tag{3.1}$$

$$Y_{\text{rural}} = 182.4735x \quad \text{when} \quad x = 10 \quad \text{(i.e., potential fee level = 10\%)} \tag{3.2}$$

The fee in urban areas is higher at £1,824.735 per year, while in rural areas, the fee is set at £763.7849 per year.

Similarly, the Volumetric Component is based on the number of cigarette sticks sold by the retailer, with a fee of £9.972 per 1,000 cigarette sticks sold, which is determined by the equation[12]:

$$Y_{\text{volume}} = 0.3324x \quad \text{when} \quad x = 30 \quad \text{(i.e., potential fee level = 30\%)} \tag{3.3}$$

This component is designed to ensure that the fee is proportionate to the retailer's actual sales activity, thereby achieving a fairer distribution of costs no matter how popular the retailer is. The volumetric fee reflects not only the sales volume but also the retailer's potential impact on the public health. The higher the sales volume, the greater the retailer's influence on the market, and thus they should bear a higher fee.

The whole complex fee structure is displayed in the following table 3.1:

Component	**Urban**	**Rural**
Urban-Rural Component	£1,824.735/year	£763.7849/year
Volumetric Component	£9.972 per 1,000 cigarette sticks sold	

Table 3.1: Complex Licence Fee Structure for Tobacco Retailers

3.2 Agents % Behaviour

Agents design and their behaviour is the soul of Agent-Based Modelling. In this section, the detailed settings of attributes & behaviours, and categories of each kind of agents will be illustrated.

3.2.1 Adult Agents

In the current ABM, adult agents represent the individual and potential tobacco consumers within the virtual town, whose behaviour significantly influences the dynamics of the simulated market. Their behaviours is modeled based on both the basic logic of purchasing products and the price sensitivity functions for the change of the smoking rate. Since one of the objectives include the analysis of smokers and the aim mentioned in framework emphasised that the smoking rate among adults should be decreased[2], the age group of 35 to 45 is selected for this study.

Adult agents are primarily classified into adult agents and previous age groups. Only the smokers will be included in the tobacco purchase interactions, non-smokers will never be taking into account, and the previous age group, which can be predicted to satisfy the age limitation during the simulation, will be added to the model when they meet the requirements. (e.g. 34 years old smoker)

The attributes of the adult agents contains:

- **Age**: Randomly generated.
- **Smoking Status**: Generated by smoking prevalence in certain area.
- **Home**: Randomly allocated according to household counts.
- **Workplace**: Randomly allocated according to business density.
- **Wage**: Generated by CDF wage distribution.
- **Money**: Generated by spending rate multiplied by monthly wage.
- **Saving Rate**: Allocated by different wage level.
- **Daily Cigarette Consumption**: Generated by smoking rate and will change according to the price sensitivity function.
- **Cigarette Inventory**: Randomly initialised and used for judgement of purchase.
- **Transport Mode**: Initialised according to the transport mode proportion.
- **Favourite Retailer**: Used for recording the favourite retailer of the agent.
- **Trip Cost**: Used for recording the trip cost for favourite retailer.

The behaviour of the adult agent mainly includes the smoking activity of themselves, the interaction with retailers and other change functions related to certain coefficient, which aim at simulating the smokers in real life. The detailed behaviours are listed below:

- **Save Money From Salary**: Used for calculating the money for tobacco purchase. Return the spending rate multiplied by monthly wage.

- **Smoke**: Used for simulating the smoking process per day. In this behaviour, agents judges whether they still have enough inventory for consumption, if it is enough, then smoke and consume the cigarette. On contrary, stop smoking this day and record the days without smoking. If there are more than 27 days not smoking, change the agent status into quitter.

- **Calculate Packs To Buy**: Used for calculating the packs to buy. First calculate the packs they want through daily consumption, then the packs they are affordable by money, and then choose the lower one.

- **Choose Favourite Retailer**: Used for choosing favourite retailers. In the model, this behaviour is designed to browse all the retailers to find agents' favourite retailer according to the distance, price, trip costs and other factors to imitate the choice of agents in real life choosing retailers near their home or workplace. This behaviour will return the favourite retailer and its trip cost, then consequently change their own daily consumption through smoking rate change according to the price sensitivity function with the PEC mentioned before in the data section (PEC - Price Elasticity Coefficient):

$$\text{Smoking Rate} = \text{Smoking Rate} \times (1 + \text{Cost Increment} \times \text{PEC}) \tag{3.4}$$

- **Buy Cigarettes**: Interaction with the retailers. First calculate the packs to buy, then finish the purchase process and change the related attributes including money and inventory. Also trigger the **Sell** behaviour of the agents' favourite retailers.

- **Calculate Average Speed**: Used for calculating the average speed of different transport modes. The data is collected from the government survey mentioned in Data section.

- **Calculate Energy Consumption**: Used for calculating the energy consumption of different transport modes. The data is collected from the government survey mentioned in Data section.

- **Get Petrol Price**: Used for getting the petrol price of different transport modes. The data is collected from the government survey mentioned in Data section.
- **Step**: Basic behaviours of the agents each day, mainly include the growing up behaviour and the wage payment per month.

To be specified, the previous age group agent only contains the age attribute and basic growing up behaviour to prepare for joining the model and the agents out of the age group will be removed.

Overall, the design of adult agents in the model have closely mimicked real-world adult behaviour in smoking area, allowing for more accurate predictions policy impacts.

3.2.2 Retailers

When it comes to the retailers, which served as the primary agents that supply tobacco products to adult agents. Their behaviour also mimicked the logic in real life, includes basic interactions with consumers, pricing strategies to compete with others and specially, paying the licence fee. Currently, this study not focus on the specific type of the retailers, therefore, the certain retailer type(e.g. petrol station retailer / pub retailer) will not be clarified and the location will be allocated randomly.

Retailers in the model are categorised into three main types: large chains, small independent stores, and noise retailers(part of small retailers with random strategies). Each type has its distinct characteristics and operational strategies, which affect how they interact with the market and respond to policy changes.

The attributes of the retailer agents mainly include:

- **Retailer Type**: Generated randomly according to the town status data.
- **Selling Flag**: Used for reflecting the current selling status of the retailer.
- **Licence Lasting Time**: Used for judging whether the licence is out of date or not.
- **Location**: Randomly allocated based on retailer density and area square.
- **Pack Cost**: Generated randomly according to the tobacco pack cost data statistics.
- **Pack Price**: Generated randomly according to the tobacco pack price data statistics. If the pack cost is higher than price by chance, adjust the price higher to make the model more reasonable.

- **Type Variant**: Either **keep_close** or **price_adjust**. Used for the clarify of the experiment type: Only price adjust / Only judge stop or not.
- **Gross Profit**: Record the gross profit per day for strategy changing and output.
- **Customer Traffic**: Record the customer traffic per day for strategy changing and output.
- **Customers**: Record all the current customers with the retailer agent itself as the favourite retailer.
- **Nearby Retailers**: Record certain numbers of nearby retailers for strategy changing. Only the data which can be obtained in the realistic situation will be recorded(e.g. pack price / customer traffic)

For retailer agent behaviours, there are some discrepancies between different types of retailers. Part of the small retailers, will definitely try to change their strategies to win the game of pricing or market share, like mentioned in the study of gilmore[9]. The other part of small retailers, which can be recognised as **noise traders**, is also existed and tend to react randomly to any kind of business situation, which consequently add more uncertainty to the market. This kind of behaviour can be inferred from the study[29]. Then, even there is a lack of actual data proof for large retailers' behaviour, they can still be classified as a kind of retailer which seldom change the strategies[30]. Large retailers have the capacity to better adapt fee scenarios due to more diversified business, bigger capacity to obtain tobacco at lower prices from wholesalers to make larger profits from tobacco sales. The common behaviours of retailer agents include:

- **Sell Cigarettes**: Interact with the **Buy Cigarettes** behaviour of the adult agents to sell the tobacco products. If the selling flag is true, which means the retailer has paid the licence fee and operate normally, the cigarettes will be sold and the sales volume and profit will be recorded.
- **Pay Licence Fee**: Behaviour for the retailer to pay the licence fee. The retailer will calculate the licence fee it should pay according to the sales volume(per stick), then renew the licence lasting time.
- **Calculate Daily Info**: Behaviour for calculating the daily information, which contains the price, profit, volume, customer traffic, licence fee, lasting time and selling flag. Used for providing the necessary data storage for strategy change.

To be specified, for the strategic behaviours, the large retailers are designed to always selling and keep the same pack price, which means the large retailers will **NEVER** change the strategy. And the noise retailer always make the random decision for each time interval at same probability. Then, the strategic behaviours of small retailer agents include:

- **Get Nearest Retailers Info**: Used for collecting the data of 3 nearest competitors which is logically accessible including their location, pack price and customer traffic. The data collected can be used in the strategy change.
- **Estimate Demand Elasticity**: Behaviour to estimate the demand elasticity, which is inspired by the studied like[31] and [32], to use it as one of the aspect to consider the strategy change. In this study, the demand elasticity is basically calculated through the customer traffic.
- **Adjust Price**: Behaviour to adjust price based on the game theory principle and related data, which will be illustrated in the next section.
- **Decide To Sell/close**: Behaviour to make a judgement on when to exit the market based on the game theory principle and related data, which will be illustrated in the next section.
- **Change Strategy**: Behaviour to change the strategy, controlled by the type variant for choosing different strategies.

These behaviours are designed to mirror the operations of real-world tobacco retailers, capturing the complexities of market dynamics and the impact of policy interventions.

Among all the behaviours, some of them change their own status and others interact with other agents. For adult agents, the most critical behaviours is choosing the favourite retailer, which will not only change the choice but also alter the smoking rate, which finally affects the whole market. While for retailers, especially the small retailers with strategic change, the key behaviour is the Choose Strategy, which will change the pricing or exiting decisions.

The whole structure of the agents of adults and retailers can be concluded into the following figure 3.2:

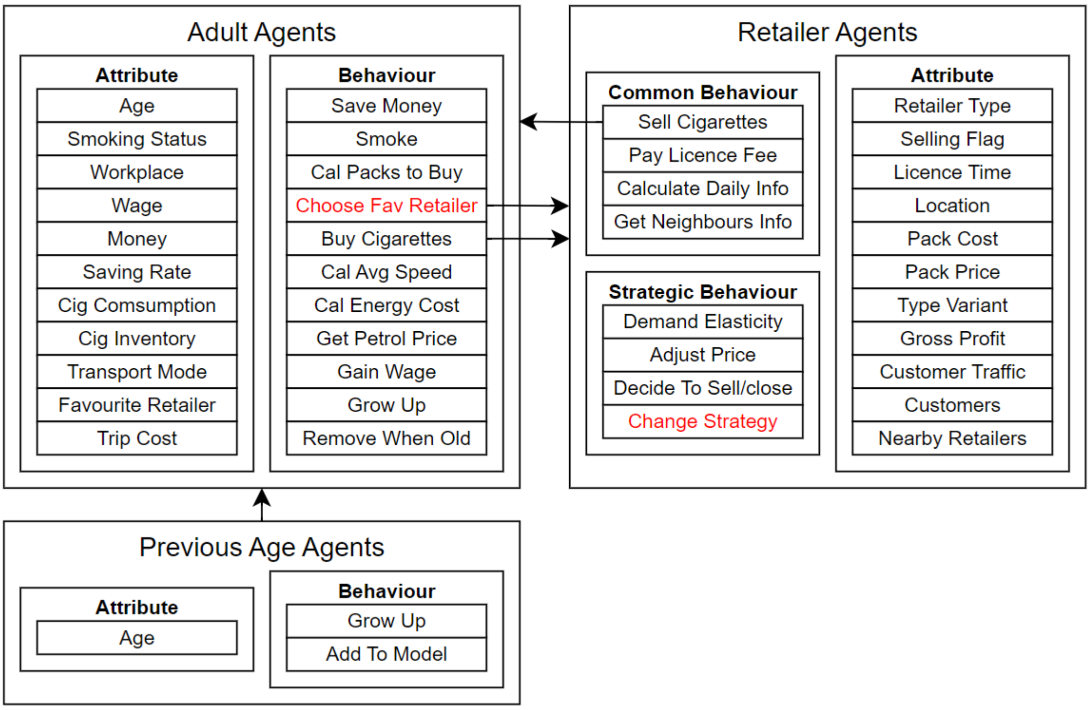

Figure 3.2: Agents Structure

3.3 Game Strategies

To set up the special strategy for small retailers, the game theory is a suitable choice. Game theory offers a powerful analytical tool for understanding market competition, which can be considered as a reference when setting up pricing strategies and market exit decisions. The fundamental assumption of game theory is that all small retailers (exclude noise retailers) are rational and will adopt optimal strategies to maximise their own benefits. And due to market uncertainties and incomplete information, retailers' strategies often involve predicting and responding to the actions of their competitors.

The game theory principle applied in this model is inspired by both the related books which explained multiple kinds of principles of non-cooperative game theory[33] and the articles about the games between retailers including [34, 35, 36, 37] etc. The former one provides the theoretical basis of the concept of the model used, while the latter ones inspired the approach to apply them in the model. The detailed design will be described below.

3.3.1 Pricing Game

When designing the pricing strategy for small retailers, the idea draws mainly from the Bertrand competition model in [33]. The model helps to build the basic pricing strategy, based on that, the Demand Elasticity[38] is used for determining the proportion of price change.

In the pricing game, small retailers must consider how their pricing strategies will affect market share, profits, and consumer behaviour.

In this study, the pricing strategy of the small retailers can be described as the following process: First, Calculate the demand elasticity according to the customer traffic of both themselves and their competitors. The equation of the calculation in this model for the small retailers inspired by the study [39] is listed below:

$$\text{Demand Elasticity} = \begin{cases} 0.5 & \text{if traffic ratio} \geq 1 \\ 1.5 \times \left(1 - \frac{\text{Average Traffic}}{\text{Average Competitor Traffic}}\right) & \text{if traffic ratio} < 1 \end{cases} \tag{3.5}$$

Then according to the demand elasticity and other information (mainly the price difference and profit loss caused by paying licence fee), the small retailer will increase / decrease its price, with a certain proportion which is related to the price difference and demand elasticity. The price renew equation is:

$$P_{\text{new}} = \begin{cases} P_{\text{now}} & \text{if } |\Delta P| < 0.05 \times P_{\text{now}} \\ P_{\text{now}} + \Delta P \times (0.3 + 0.7 \times E_d) & \text{if } \Delta P > 0 \ \& \ \Pi_{\text{now}} \geq F \\ P_{\text{now}} + \Delta P \times (0.5 + 0.5 \times E_d) & \text{if } \Delta P > 0 \ \& \ \Pi_{\text{now}} < F \\ \max\left(P_{\text{now}} + \Delta P \times (0.7 + 0.3 \times E_d), P_{\text{cost}}\right) & \text{if } \Delta P < 0 \ \& \ \Pi_{\text{now}} < F \\ P_{\text{now}} & \text{if } \Delta P < 0 \ \& \ \Pi_{\text{now}} \geq F \end{cases} \tag{3.6}$$

Where: P_{new} represents the new pack price. P_{current} represents the current pack price. ΔP represents the price difference compared to competitors. E_d represents the demand elasticity. Π_{current} represents the current profit. F represents the licence fee. P_{cost} represents the pack cost.

In this pricing strategy, the game theory principles involved mainly include bounded rationality, signaling theory, Bertrand competition model and Dynamic Pricing Model[33].

Bounded Rationality plays a significant role since retailers do not have perfect information or unlimited cognitive capabilities to make fully rational decisions. Instead, they operate with limitations of how much information they can obtain, making decisions that are satisfying rather than optimal. This is reflected in how small retailers adjust their prices based on nearby competition rather than the entire market.

Signaling Theory is relevant to how retailers set their prices to send signals to competitors. By adjusting prices in response to competitor pricing, retailers signal their strategic purpose, such as their willing to engage in price wars or maintain a normal position, then the competitors will make a response in turn to send their signal, causing the signaling game.

The **Bertrand Competition Model** explains the basic assumption that retailers compete by setting prices, and consumers choose the retailer offering the lowest price and trip cost. This model explains the aggressive price adjustments phenomenon among small retailers who aim to capture market share from competitors by offering more attractive prices.

Finally, **Dynamic Pricing Models**, similar to the former one, reflect the iterative nature of pricing decisions over time. Retailers continuously adjust their prices based changes in market conditions, competitor behaviour, and their internal profit metrics. This dynamic adjustment process is critical for understanding how prices evolve in response to both internal and external pressures.

3.3.2 Exit Games

In designing the market exit strategy, the idea drew from the War of Attrition model in [33] and the Mini-max Regret theory in [37]. These theories help simulate small retailers' exit decisions and the usage will be illustrated in the following part.

In the context of keep-close variant, the decision to exit the market, particularly for small retailers, is influenced by several factors including profits, licence fee and competitor information. The logic behind the exit game revolves around assessing whether it is more beneficial under low-profit or fierce competition conditions.

The exit strategy of small retailers can be described as follows: First, the model evaluates the retailer's current profit, which is compared against licence fee. If the profit is significantly lower than the cost, the retailer may consider exiting the market. Additionally, the current operating status which can be observed by customer traffics and sales volumes, is also a critical factor that should be take into account. The equation of exiting games is listed below:

$$\text{Exit Decision} = \begin{cases} \text{Exit} & \text{if } \Pi_{\text{current}} < \frac{F}{4} \ \& \ P_{\text{avg}} > P_{\text{comp\_avg}} \ \& \ T_{\text{avg}} < T_{\text{comp\_avg}} \\ \text{Exit} & \text{if } S_{\text{avg}} < S_{\text{avg\_past}} \ \& \ T_{\text{comp\_avg}} > T_{\text{avg}} \\ \text{Exit} & \text{if } \Pi_{\text{current}} < 0.5 \times \Pi_{\text{comp\_avg}} \\ \text{Stay} & \text{Otherwise} \end{cases} \tag{3.7}$$

Where: Π_{current}: Current profit over the last time frame (e.g., 90 days which is longer than pricing games since exit decision should have a longer term judgement). F: Licence fee. S_{avg}: Average sales volume over the last time frame. $S_{\text{avg\_past}}$: Average sales volume over the previous time frame (e.g., from 180 to 90 days ago). T_{avg}: Average customer traffic over the last time frame. $T_{\text{comp\_avg}}$: Average competitor traffic over the last time frame. P_{avg}: Average pack price. $P_{\text{comp\_avg}}$: Average competitor pack price. $\Pi_{\text{comp\_avg}}$: Average profit of the nearest competitors over the last time frame.

The specific rules implemented in this model are inspired by game theory principles[33], mainly involved War of Attrition, Bounded Rationality, and Mini-max Regret.

War of Attrition is a game theory model where competitors endure losses for a period (in this study means profit lower than licence fee), hoping that their competitors will earlier to exit the market. In the context of small retailers, this model is relevant since they may choose to stay in the market despite low profits, hoping competitors to quit first, thus reducing competition and allowing them to capture more market share. This strategy is risky but rewarding if the retailer can insist until its competitors leaves.

Similar to the pricing, **Bounded Rationality** also applies here. They operate with a limited understanding of their competitors' strategies and the broader market conditions. This limitation influences their exit decisions, as they may opt for doing nothing (insist a decision that is good enough) rather than optimising their strategy.

Mini-max Regret is another relevant concept in game theory in this context, which involves making decisions that minimise the potential regret from a worst-case scenario. For small retailers, this means choosing a strategy that would have caused the least regret if competitors have better performance than them or if market conditions get worse. This approach often leads to conservative decision-making, where the retailer may choose to exit the market to avoid significant future losses.

One thing that should be noted is that all these strategies mentioned above is for the small retailers in current ABM, For large retailers, they never change strategy due to their solid background, and for noise retailers, they make random choices at same probability.

Chapter 4

Implementation

4.1 Experiment Design

In this study, the experiment design is crafted with the objective to evaluate the effectiveness and accuracy of Agent-Based Model (ABM) in simulating the impact of tobacco licence fees on retailer behaviour and market dynamics in urban and rural areas with different retailer strategies. The experimental framework is divided into two primary groups, each account for a different direction, including Pricing and Exiting.

The first experiment group focuses on pricing strategies. The primary objective is to observe how these retailers react when faced with tobacco licence fee policy. The variables include the retailer strategy and area type. The experiments will be conducted separately for urban and rural environments to account for the differences in market size, customer density, competition intensity and other related factors. Key metrics such as sales volume, gross profits will be tracked to assess the impact.

The second experiment group basically remains the same as how the first group goes except for the retailer strategies change from pricing to exiting strategy the market, which will also be simulated in both urban and rural areas. The variables include the retailer strategy and area type.

The methodology for conducting these experiments involves initialising the model with real-world data relevant to urban and rural market conditions, followed by running simulations over a defined period. The lasting period of the simulation is designed to be 5 years, to see a long-term result. To be noted, the data (illustrated in the data section) is normally provided in division of SIMD or Urban/Rural-Most/Least Deprived, so when taking these data into account, the validation (in the next section) process is indispensable. The model will be calibrated using historical data to ensure its accuracy in reflecting actual market behaviour. As aforementioned, related data will be collected. The results will be demonstrated using plots and analysed to determine the model effectiveness for evaluating the impact of licence fees.

Through the above experimental design, this study provides a comprehensive evaluation of the impact of the policy under different circumstances. These experiments can offer valuable decision support for policymakers, aiding them in understanding the market response from the retailer's sight. The results and analysis will be detailed in the next chapter.

4.2 Model Validation

Model validation is a crucial proportion in this study, to ensure that simulations accurately reflect real-world behaviours and outcomes from the data aspect. Without proper validation, the predictions (simulation results which represents future developments) could be unreliable or misleading, potentially causing incorrect conclusions and ineffective policy recommendations. Through the process of validation, we can confirm that the data used for initialising the model are grounded in reality (with no licence fee), thereby increasing confidence in the predictions for analysing the impact of licence policy. Additionally, validation helps to identify any discrepancies and limitations between the model and real-world data, allowing for necessary adjustments and thoughts for future improvements.

Under current circumstances of the study, model validation was performed using a basic environment without policy to mimic the real-world environment and simulating for 5 years to get the data and compare it with realistic data to see whether it has gentle discrepancies or huge gaps. This base scenario is a straightforward simulation where retailers sell tobacco products as usual with no strategy changes, and smokers purchased them normally. Over the five-year period, we tracked the data in each type of town (urban, rural), then compared them with historical sales data gained from Scottish government surveys(see Data section 3.1.2), which divided by town type. This comparison allowed us to assess how closely the model's outputs aligned with actual sales data to achieve the goal of validating the model initial values for generating all the parameters needed.

4.2.1 Data Weight

The raw data obtained from the studies and surveys mentioned in section 3.1.2 was originally classified into Urban-Most Deprived, Urban-Least Deprived, Rural-Most Deprived, Rural-Least Deprived, or separated by SIMD, so how to get the data which can clearly mirror the realistic situation of urban and rural area is the critical problem. The data weight is a reasonable approach to solve it. In simple terms, the urban data equals Urban-Most Deprived data multiplied by the weight of UMD, plus Urban-Least Deprived data multiplied by the weight of LMD, and the data for rural area is computed in the same way but with Rural-Most Deprived, Rural-Least Deprived data. The equation is displayed below:

$$\text{Urban Data} = (\text{UMD} \times W_{\text{UMD}}) + (\text{ULD} \times W_{\text{ULD}}) \tag{4.1}$$

$$\text{Rural Data} = (\text{RMD} \times W_{\text{RMD}}) + (\text{RLD} \times W_{\text{RLD}}) \tag{4.2}$$

$$W_{\text{UMD}} + W_{\text{ULD}} = 1 \quad \text{and} \quad W_{\text{RMD}} + W_{\text{RLD}} = 1 \tag{4.3}$$

Where: UMD: Urban-Most Deprived data. ULD: Urban-Least Deprived data. RMD: Rural-Most Deprived data. RLD: Rural-Least Deprived data. W_{UMD}: Weight of Urban-Most Deprived data. W_{ULD}: Weight of Urban-Least Deprived data. W_{RMD}: Weight of Rural-Most Deprived data. W_{RLD}: Weight of Rural-Least Deprived data.

When calculating the initial data through this formula for base simulation, we can get the specific result for the comparison with actual data, and choose the one most close to it. The result will be displayed in the following section.

4.2.2 Data Calibration

Except for the data divided into 4 types, there are still some other data need to be calibrated, like the prevalence or quitting rate, etc. For those data, there are some studies published by some research teams including [40, 41], The research team initially segmented the available data into more specific parts, like the UMD to RLD class mentioned before, and then merge then according to the population data from the Scottish Household Survey with the distribution of relative (lower than 60% UK median income) and severe poverty (lower than 50% UK median income) to ensure the data is reflected in the model. By combining these classifications with poverty-level data, the research team derived weights for broader categories which can be used in the model.

These weights ensured that the data inputs were accurately represented to reflect the true distribution across different areas in Scotland.

The smoking prevalence data which incorporated into the model were obtained from the 2022 Scottish Health Survey and the Scottish Household Survey, utilising the Scottish Index of Multiple Deprivation (SIMD) to accurately represent smoking prevalence and quitting rates across various area types[42, 43, 44]. With calculated through certain weight, the related data can be applied to the current ABM. The results will be displayed in the following section (4.2.3)

Some of the data has the problem of neglecting the certain portion of the real data in rural areas[45], causing the difference between data. To solve such kind of potential inaccuracies, the calibration applies a method for ensuring the data used in the model always falls in the 95% confidence interval. And the z-score will be calculated to make the data more reliable. The final validation result shows the robustness and accuracy of the model, which will be showed in the following section (4.2.3)

4.2.3 Validation Results

All the validated data mention before can be summarised into this table, which shows both the reasonable data used for generating and initialising the models and the base simulation result for visualised validation attributes. The data is listed in the table 4.1 below.

The conclusion can be indicated from the results that the model demonstrated certain consistency with historical data during validation in the urban and rural areas. The difference shown in the result between the model's average sales and actual data is less than 10%, which shows the accuracy of the related pre-processing procedure.

The results show that smoking prevalence is higher in urban areas, which is consistent with real-world conditions. Meanwhile, the slightly lower average sales volume in rural areas reflects the more relaxed competitive environment for retailers and the different behaviours of consumers. The model appropriately weighted retailer density for urban and rural areas, which is crucial for ensuring consistent performance of initial data across different regions.

However, some minor deviations can be observed in the model results, particularly in rural areas, may be due to the inability to fully capture region-specific factors, which just conform to the study mentioned before. Additionally, the model uses current prevalence when predicting future situations without considering the natural decline,

Data	Urban	Rural
Grid Size	38*38	206*206
Retailers	Small: 39, Large: 2	Small: 67, Large: 1
Prevalence	18%	15.35%
Pack Price	10.615	11.057
Total Sales (Model)	1,798,413.75	1,650,319.95
Avg Sales (Data)	42,206.26	26,300.32
Avg Sales (Model)	43,863.75	24,269.411
% Difference	-3.78	8.37
Z-Score for 95% CI	0.01	-0.09
Ideal Range	-1.96 to 1.96	-1.96 to 1.96
Population	20,000	20,000
Age Prop (35 to 45)	12.5%	12.5%
Area Weights	$W_{\text{umd}} = 34$, $W_{\text{uld}} = 66$	$W_{\text{rmd}} = 26$, $W_{\text{rld}} = 74$

Table 4.1: Urban and Rural Data Validation Results Summary

which might result in slightly lower data compared to historical one. Nevertheless, the model compensates for this to some extent by capturing the influence of non-smokers on existing smokers in the model.

Overall, despite some challenges, the model's output aligns with the historical data, confirming its accuracy in simulating current project on licence fee policy model.

4.3 Simulation Process

The simulation process in this study is the complete procedure of the ABM setting up and running to replicate the interactions between various agents within a virtual town, then record the simulation result to observe the impact of tobacco licence fees policy. The simulation proceeds through several key stages, including initialisation, execution, and result collection, which are discussed in detail below.

4.3.1 Initialisation

During the initialisation phase, the simulation environment is set up based on the data generated and validated by the real-world data (mentioned in 3.1.2 and 4.2). Agents, including retailers and adult consumers, are created with attributes generated from the processed and validated data. Data loading and parameter settings are done through the data loader module, ensuring that the simulation starts with realistic baseline conditions.

4.3.2 Execution

The execution phase of the simulation involves the dynamic interactions of behaviours between agents over 1800 steps, with first 360 steps not applying policy. Each time step, agents execute their behaviours (mentioned in chapter 3.2) based on predefined rules which are implicit in the model. Retailers adjust prices using strategies derived from game theory while adult agents make purchasing decisions based on their smoking habits and financial situation. The simulation processes these interactions iteratively, updating the state of the market and the agents at each step.

4.3.3 Result Collection

During the execution process, the daily information of all the main attributes and the parameters will be recorded to the certain data structure. At the end of each simulation run, these results are plotted or calculated for analysis. Key metrics such as sales volumes, gross profits, pack prices, licence fees, the number of retailers remaining in the market and the number of quitters among all the adult agents are all collected for analysis. The collected data will be then analysed in the next chapter (chapter 5) to assess the impact of tobacco licence fees policy. The analysis will mainly focus on the retailers under urban and rural scenarios, as well as different retailer strategies.

The whole simulation process can be described by the figure 4.1 below:

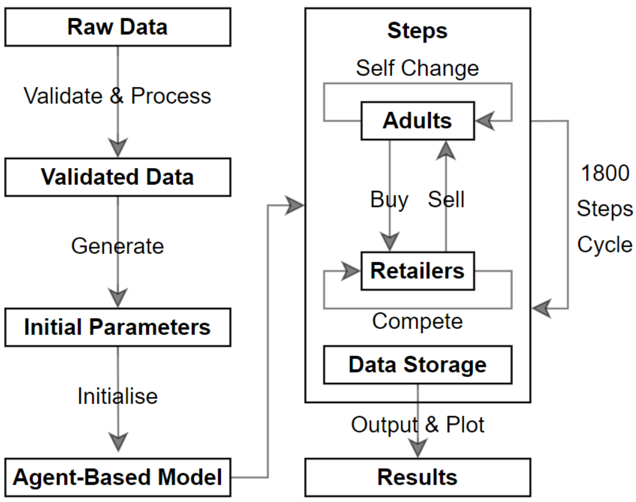

Figure 4.1: Simulation Process From Data Process To Modelling Simulation

Chapter 5

Results & Analysis

In this section, the result of ABM simulation for 5 years will be concluded and displayed in 3 parts, Retailers, Adult Agents and the Uncertainty. Then the certain results will be analysed including the phenomenon observed in the results, the causes of formation, and the findings and implications based on them.

5.1 Simulation Results

5.1.1 Uncertainty

At the very beginning, the uncertainty of the model must be clarified. Despite all the data is already validated, the simulations which are far from real-world logic and could be judged as unqualified may appear at a relatively high probability, especially for the large and noise retailers.

The representations of the unqualified mainly includes extremely remote location (e.g. coordinate [1,1] in rural areas) and all the collectable attributes remains zero, with no change during the whole process. This kind of simulation results will be excluded from the studies' common statistic results. One of the example of the large retailer data (in the certain location of [2, 13] in Rural area) is shown in the following figure:

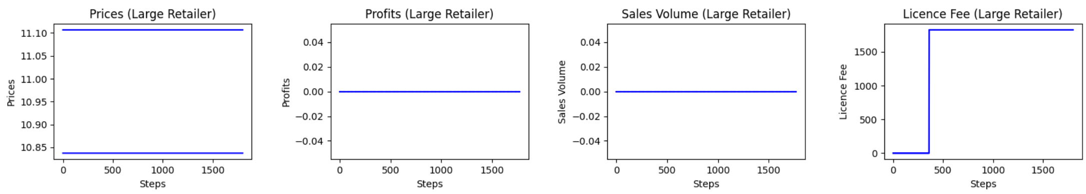

Figure 5.1: Unqualified Simulation - Large Retailer Changing in 5 Years

The plot above shows the changing of the Pack price, Gross Profits, Sales Volumes and licence Fee during the 5-year simulation. In 5.1, the profits and the sales volume are always zero during the simulation, and the licence fee only contains the basic area component, indicating that the large retailers have no customers at all with remote locations, which is quite unreasonable.

5.1.2 Retailers

For the retailers, there are 3 different types of them under 2 regions with 2 strategy research type, which stands for **Large Retailers, Small Retailers, Noise Retailers** within **Urban or Rural** areas allocated with **Price Adjust or Market Exit** strategies.

For each scenario, the result for the retailers will include one plot with all the critical attributes of 3 types of retailers, and another plot separately demonstrate their own trends. The main attributes contains: Price Adjust Plot, Gross Profits Plot, Sales Volume Plot and Licence Fee Plot. To make the result clearer, the daily profit and volume is plotted through the average monthly value, with maximum and minimum value in the separated plot. The result shown here is carefully selected after running the simulation for more than hundreds of times for choosing the one which can reflect the real-world situation. And for the randomness of the ABM, the detailed data changing proportion can not be displayed precisely. Instead, there will be a range to record the diversification of the simulation.

The result figure for the retailers which contains all the data plots including 5.2, 5.3, 5.4, 5.5 in Experiment Group 1 and 5.6, 5.7, 5.8, 5.9 in Experiment Group 2 will be illustrated in advance.

For the first figure type named by **[Area-Type-Combined Data Plot For All Retailers]** (5.2, 5.6, 5.4, 5.8), the figure consists of 4 plots which combine the simulation results of all types of retailers.

- The up-left plot shows the price change of each single retailer during the 5-year simulation.
- The up-right / bottom-left plot shows the average monthly profits / sales volume change among 3 types of retailers during the 5-year simulation, and the value per step is averaged for each type to make the curve clear to observe.
- The bottom-right plot shows the licence fee change of each single retailer during the 5-year simulation.

For the second figure type named by **[Area-Type-Separated Data Plot For All Retailers]** (5.3, 5.7, 5.5, 5.9), the figure consists of 12 plots which demonstrate the simulation results of each type of retailers separately. Each row represents a type of retailer(Row 1 - Large, Row 2 - Small, Row 3 - Noise)

- The first plot in each row shows the price change of each single retailer in specific type during the 5-year simulation.
- The second / third plot in each row shows the average monthly profits / sales volume change with maximum and minimum value to observe the special instance as well as the changing range of each type.
- The fourth plot in each row shows the licence fee change of each single retailer in specific type during the 5-year simulation.

For the Experiment Group 1 simulation in urban area, which represents the Price Adjust strategy, the retailer results are demonstrated as follow:

- Some of the small retailer's prices keeps its level, others have the same changing trend with specific noise traders, but at a lower proportion. The large retailer never change its price.
- The sales volume for the retailers in the second year will decrease dramatically ranging from 40% to 70% comparing with the first year after applying the licence fee policy (e.g. 35500-11680 sticks 67.1%). From the third year, the data will fluctuate with the range of 20% to 50% in contrast to the last year.
- The sales profit, which related with the sales volume to some extent, has the similar trend with the sales volume. But noise retailers may show a possibility to have a higher volume with lower profit.
- For the licence fee change, there is a trend to dive in the second year when paying the licence fee for the first time, and then become smooth in the next 3 years. Usually, the small retailer with the game-theoretic price changing strategy may have the highest licence fee.
- From the retailer type difference, the large retailer will have a better performance if the location is generated properly, while the small retailers keep relatively stable data comparing to the noise ones, but always worse than the large retailers.

- For the maximums and the minimums, the small retailer has the best and most stable performance of maximum, while other retailers' data keeps fluctuate. For the minimums, the small retailers also have the worst performance (maybe unqualified results).

- There are certain numbers of spikes which can be observed in the result, especially for the large and noise retailers.

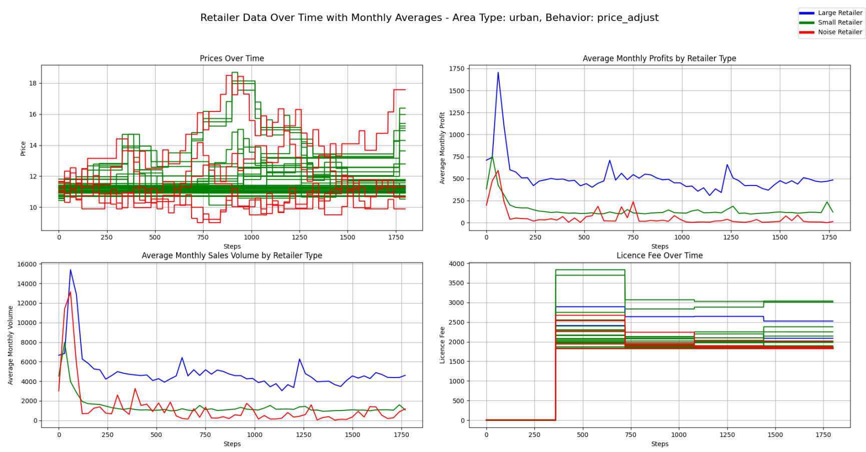

Figure 5.2: Urban-Price Adjust-Combined Data Plot For All Retailers

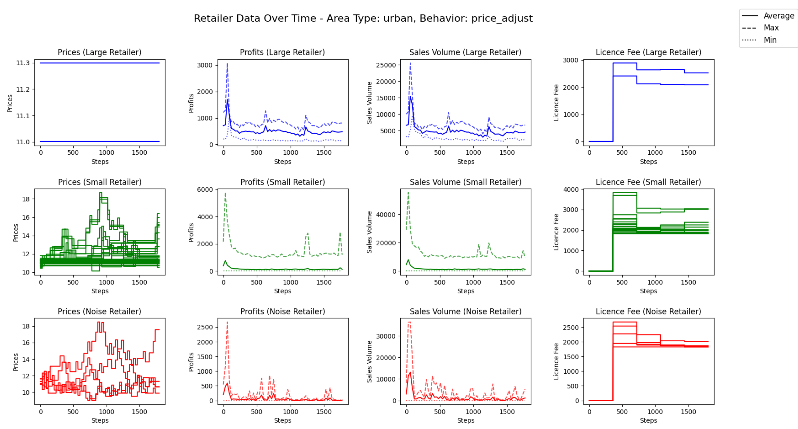

Figure 5.3: Urban-Price Adjust-Separated Data Plot For All Retailers

For the Experiment Group 1 simulation in Rural area, which represents the Price Adjust strategy, the retailer results are demonstrated as follow:

- In this experiment, the large retailer is more likely to have an unqualified simulation result.

- The sales volume trend is similar to the experiment group 1 Urban, but the changing at the first few months will be fiercer and milder in the next 4 years.
- Licence fee change trend is similar to the experiment group 1 Urban, but the noise retailers usually shows a continuously decrease tread, while the small retailers may have the chance to grow again.
- Differences between retailer type is similar to the experiment group 1 Urban,but small & noise retailers are more likely to surpass the large retailers in some cases.
- Not much gaps between the maximum and the average
- Relatively less spikes for large and small retailers.

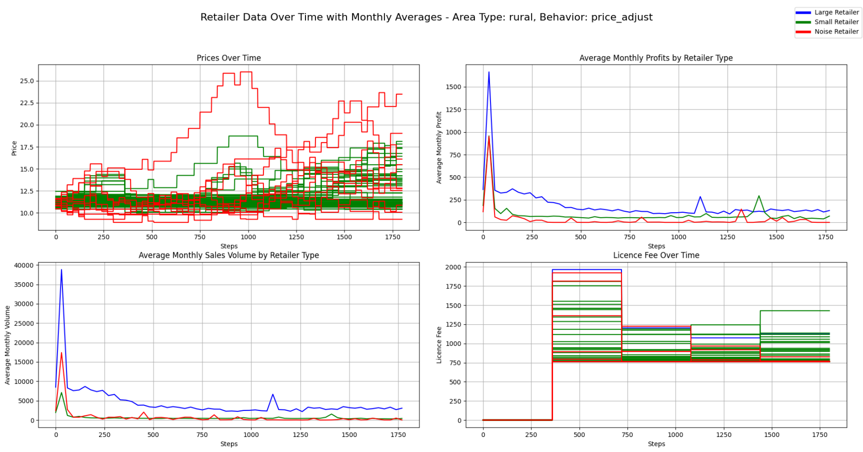

Figure 5.4: Rural-Price Adjust-Combined Data Plot For All Retailers

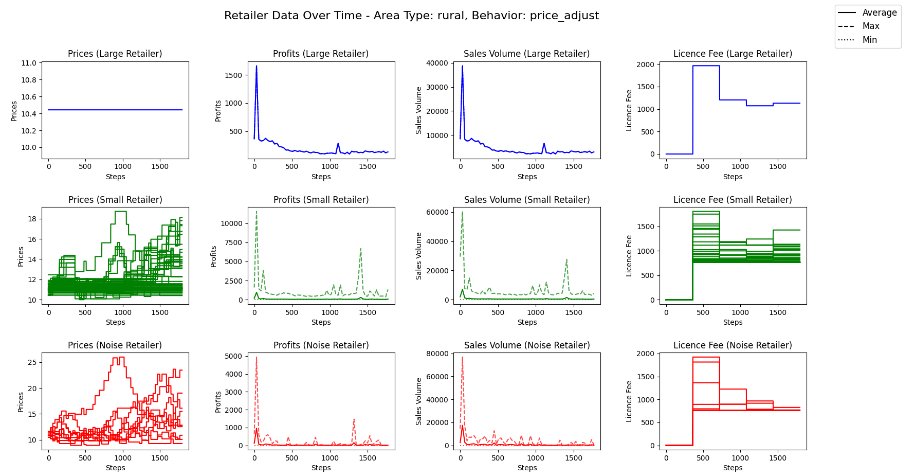

Figure 5.5: Rural-Price Adjust-Separated Data Plot For All Retailers

For the Experiment Group 2 simulation in urban area, which represents the Market Exit strategy, the retailer results are demonstrated as follow:

- The sales volume has a sightly higher decrease ranging from 30% to 75% comparing with the first year after applying the licence fee policy (e.g. 1094440-315020 sticks 71.2%). From the third year, the data will fluctuate with the range of 20% to 60% in contrast to the last year.
- Licence fee change trend is similar to the experiment group 1 Urban, but the small and noise trader have more probabilities to have 0 licence fee (Closed).
- Less spikes but sharper
- The noise retailer have the probability to completely closed.

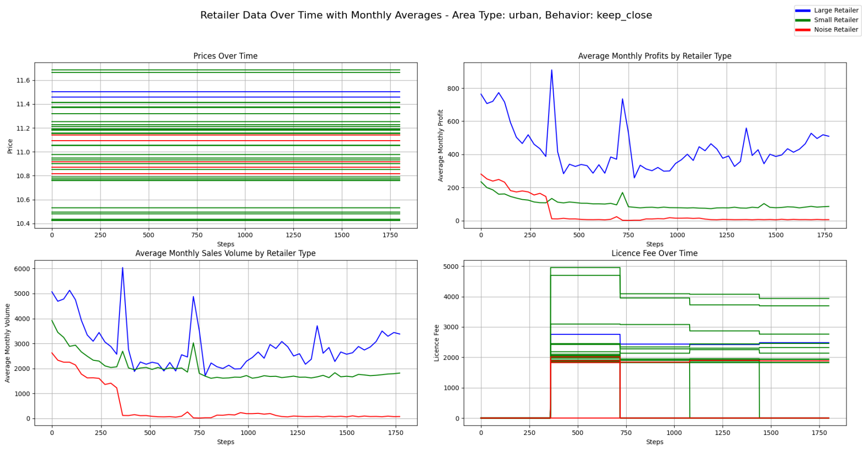

Figure 5.6: Urban-Market Exit-Combined Data Plot For All Retailers

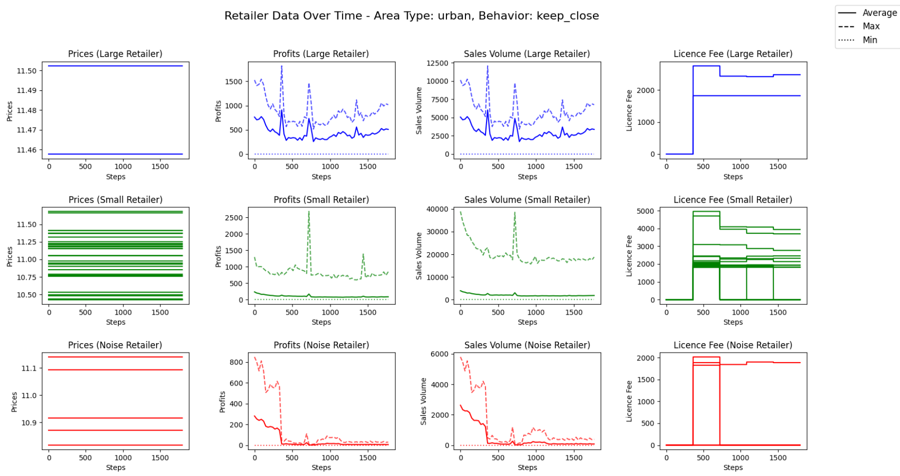

Figure 5.7: Urban-Market Exit-Separated Data Plot For All Retailers

For the Experiment Group 2 simulation in Rural area, which represents the Market Exit strategy, the retailer results are demonstrated as follow:

- Licence fee change trend is similar to the experiment group 2 Urban and the highest value belongs to the small retailer type.
- The maximums and the minimums have a huge gap for small retailers.
- Less spikes than experiment 1 and less sharper than experiment 2 Urban.
- The noise retailer have the probability to completely closed.

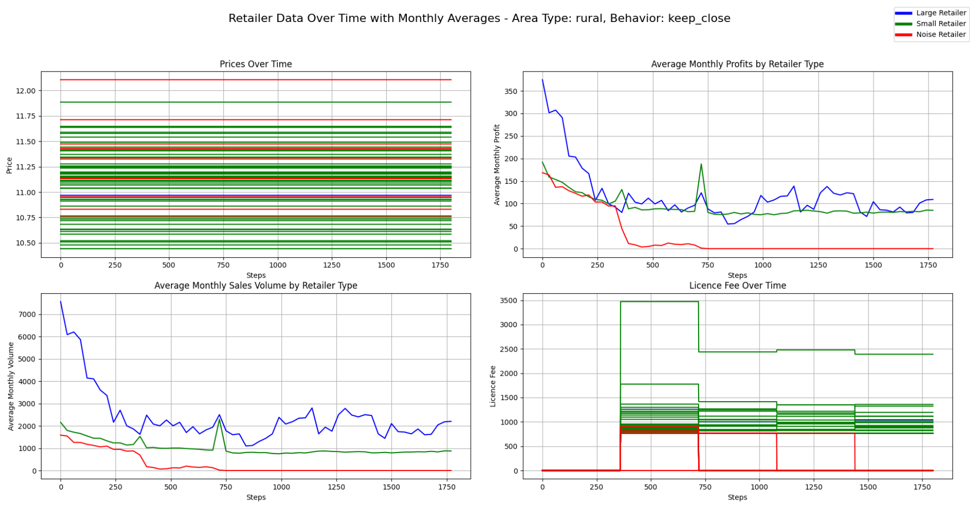

Figure 5.8: Rural-Market Exit-Combined Data Plot For All Retailers

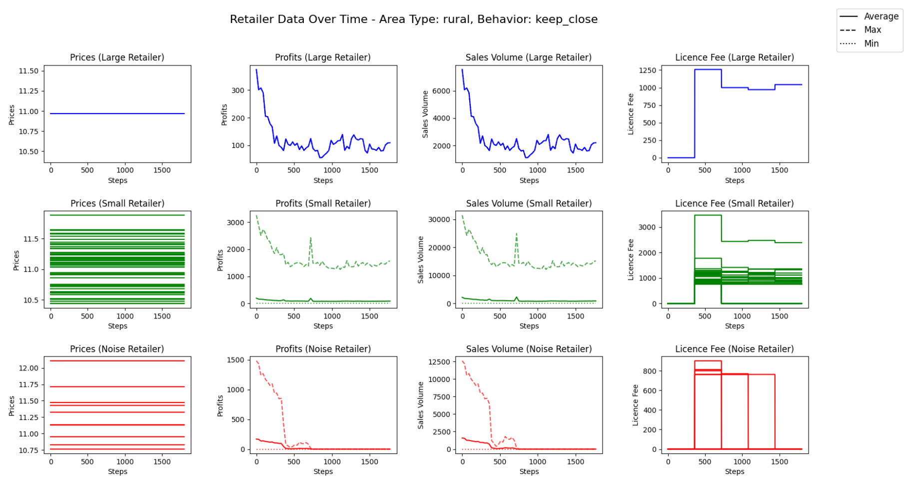

Figure 5.9: Rural-Market Exit-Separated Data Plot For All Retailers

5.1.3 Adult Agents

For Adult Agents, only the data for smokers and quitters are necessary. And in this model, the quitting rate of the adult agents means the proportion of quitters among all the original smokers at the end of the 5-year simulation, which can be calculated through the equation below:

$$\text{Quitting Rate } (\%) = \left(\frac{\text{Number of Quitters}}{\text{Original Number of Smokers}} \right) \times 100 \tag{5.1}$$

Through the quitting rate, the effect of the licence fee policy can be accessed to some extent. To get the quitting rate for 5 years in different experiment groups, the model has simulated for several times to gain the related data:

- Exp 1 - Urban Price Adjust: 5 years Quitting rate ranging from 45% to 71%
- Exp 1 - Rural Price Adjust: 5 years Quitting rate ranging from 45% to 66%
- Exp 2 - Urban Market Exit: 5 years Quitting rate ranging from 30% to 40%
- Exp 2 - Rural Market Exit: 5 years Quitting rate ranging from 41% to 48%

Other attributes are actually associated with the retailers simulation result, like the daily consumption and packs to buy, etc. and can be analysed through the Retailers' results.

5.2 Analysis

5.2.1 Price Adjust

Urban Areas: Retailer Pack price shows the same trend for both areas with the large retailers remains unchanged, and small retailers has the same trend with the noise trader when raising / reducing the price. This phenomenon is caused by the rules of pricing change. For the large retailers, price is solid to mimic their strong power in the market that supports them to not changing the price. Then, while the noise retailers randomly changing their price, the small retailers will react to such behaviour as mentioned in the game theory section (chapter 3.3).

For the sales volume and the gross profits, all the results shows a huge spike at the beginning of the simulation and then neutralised. The decreasing trend is also similar, This phenomenon can be attributed to the cost increase caused by the licence fee being passed on to consumers, thereby reducing demand. The sharp drop in sales volume indicates that consumers are more price sensitive, especially when costs increase, which also aligns to the price sensitivity function designed in the model. At the same time, the 30 days (steps) time interval of wage payment and money saving may stimulated the tobacco purchase behaviour and in turns caused the spikes at the beginning, then with frequently price adjusting games between retailers and their neighbours, though some of the customers will re-choose the favourite retailers, the data will not change significantly, except for the licence fee payment time in each year.

When talking about the licence fees data, one thing should be clarified is that it is closely related to the sales volume since the policy of complex licence fee is used. During the days without licence fees, the sales volume is much higher, which cause the licence fee grows. Then, with the procedure of gently transfer this part of the cost to the smokers, the demand of them will decrease as mentioned before, causing the sales volume to increase as well as the licence fee. In the following years, there are fierce competitions, for pricing, but the sales volume will never come back to the original height, however, there will still exist 'winner' of the game, which can be seen in the result in the last section, the sales volume increase and so does the licence fee.

For retailer differences, a special point for the noise retailers must be clarified, that is, before the licence fee was applied, the noise may take advantage by lower their price by chance. Nevertheless, after the policy applied, they could not obtain any superiority due to the loss brought by the licence fee. which causes their sales volume and profit fluctuating. And another thing need to be noted is that the curve in the result is represented in average value, so some of the performance (especially the extraordinary ones like the maximum curve represents) might be under estimated. The lower line does not means completely worse than another.

Performance differences between retailers is observed in the results, large retailers perform better with the promise that they are in favourable geographical locations. Small retailers, while more stable than noisy retailers, still lag behind large retailers in profitability and sales stability.

For the quitter rates of the agents in experiment group 1 in urban area, the quitting rate is relatively higher, since the price change will finally be imposed to the customers, and leading to the reduce of the adult agents' smoking rate and affect the daily consumption. And after 5 years simulation, the consumption is reduced to zero for more than 27 days, which improves the quitting rate.

Rural Areas: Results in rural areas were similar to those in urban areas in terms of price adjustments and sales & profit trends, but the initial decline in sales was more significant and the subsequent recovery was more modest. This suggests that rural markets are more sensitive to price changes, possibly due to lower consumer density and less competition in rural areas due to relatively larger area.

At the same time, for the retailer gaps, some of the small retailers, which can be recognised as 'winner' seem to have more chance to survive in rural area from the result. A better location is more important in rural areas since the trip cost have greater chance to be higher.

For the quitter rates of the agents in experiment group 1 in rural area, the quitting rate is also high, but is relatively lower than the urban area. And sometime not stable. The reason under this phenomenon is that the retailers behaviour in the certain 'perfect' location, which means that the retailer may have a lot of residence near itself, then its strategy will significantly affect the quitting rate. For example, if the retailer is a small retailer with game-theoretical pricing strategies, it will have a lot of customers and gain high customer traffic, with such advantages, the retailer will not change the price, causing the customers be a faithful smoker, with seldom smoking cost changes (Only threat is the licence fee). On contrary, if it is a random retailer, the price may raise price continuously, causing customers' smoking cost increase and stop smoking.

5.2.2 Market Exit

Urban Areas: First of all, in this experiment group, for the pricing part, all retailers keeps the same price, which reflects the essence of this strategy, which is a shift in focus from price competition to survival. When there are fewer competitors in the market, price stability increases because retailers no longer need to engage in fierce price wars to gain market share.

For the sales volume and profit part, retailers in this group have a lower start similar decrease trend like the first experiment group. And also, since the primary alternative only happens when paying the licence fee, the vitality of group 2 is much lower. From the result, we can observed the decline and fluctuation in both sales volume and profit. This may be due to the reduction of competitors in the market, which limits consumer choices and leads to the loss of some customers.

For the spikes in the curve, it is basically formed by the customers of the exited retailers. These 'new' customers will find the nearest retailers, forming the spikes and making it sharper. and with spikes, the licence fee will have a higher value for the specific retailer, that may accounts for the extraordinary licence fee level in the result.

The gaps between the retailers can be observed in the results. For noise retailers, they have the worst performance, since they will randomly exit the market, and the small retailers have a huge group but only seldom of them can be the hub in the simulation. While the large retailer seems to be a strong competitor, it still depends on whether the location is good or not (judged by residence nearby).

The quitting rate in group 2 in urban area can be considered to be the worse among 4 situations, with the less change in smoking cost caused by the stable operating during the year (only change when paying licence fee), and rather small areas (lead to lower trip cost when changing favourite retailer), the whole environment can form a relatively stable approach to continue smoking. (quitting rate: 30% to 40%)

Rural Areas:

In experiment group 2, there is not much difference between the urban and the rural areas besides the spikes in the curves. In rural areas, the trip cost is higher than urban, which means lower price is less attractive, when a retailer quits the market, its neighbour will absorb all its customers, thus lead to higher sales, which is the sharper spike in the curves in results.

For the quitting rate, the experiment group 2 in rural area can be the third among all 4 types. On one hand, it is higher than group 2 urban due to the higher trip cost caused by sparse allocation of retailers, which makes it higher than the former one. On the other hand, comparing to the price adjust strategy in group 1 for adjusting price per month, the time interval of making decisions for paying licence fee is too long, which offers a stable period during the year for the smokers to continue smoking.

Overall, the licence fee has a significant impact on the retail market in both urban and rural areas under different strategies. The main effect of it is to add burden to the retailers and finally reduce the smoking prevalence. From the simulation result of the ABM, it can be confirmed that, the licence fee policy is useful and have the capacity to achieve its goals under various circumstances.

Chapter 6

Conclusion

6.1 Conclusion

This study is mainly about the application of building an Agent-Based Model (ABM) to investigate the impact of tobacco retailer licence fee policies on both retailers and adults in certain age group. Through a combination of game theory and extensive simulation methodologies, the study presents a relatively comprehensive analysis of the tobacco retail market in a virtual environment that mimics real-world scenarios.

The literature review part illustrates the significance of tobacco retail in public health and the potential of licence fees as a tool for tobacco control. Previous studies have highlighted the importance of reducing tobacco availability and the role of pricing strategies in influencing consumer behavior. Based on this foundation, this study focuses on how different types of retailers—large chains, small independent stores, and noise retailers—respond to the introduction of licence fee policy, and how these responses subsequently affect the market dynamics.

The methodology outlines the structure and design of the ABM, which simulates interactions between retailers and consumers in a virtual town. The model contains various data inputs, including real-world pricing, sales volumes, and demographic factors, to ensure accuracy and relevance. Additionally, game theory principles are applied to model the strategic decision-making processes of retailers in price adjustments and market exit scenarios. This approach allows the model to capture the complexities of the market, including the competitive strategies of different retailers.

The implementation of the model involved several experiments under different circumstances to evaluate the impact of the licence fee policy in both urban and rural settings. The results demonstrate that the introduction of a licence fee leads to significant shifts in tobacco retailer market, particularly among retailers who are more sensitive to cost increases. The simulations show a reduction in sales volumes and gross profits, which are more obvious in rural areas where retailer density is lower. Moreover, the impact on smoking rates is evident, with a significant number of consumers either reducing their consumption or quitting altogether as smoking cost rise.

The analysis of these results underscores the effectiveness of the licence fee policy as a tool for tobacco control. By increasing operational costs through licence fee, the policy not only pressures retailers to adjust their strategies but also indirectly encourages consumers to reduce their tobacco use. The findings suggest that such a policy could be a crucial element in broader public health initiatives aimed at reducing smoking prevalence. Furthermore, the research highlights the importance of considering geographic differences when implementing such policies, since the impact varies significantly between urban and rural areas.

In conclusion, this study provides strong evidence supporting the use of Agent-Based Models in licence fee policy analysis, particularly in the context of public health. The ABM developed in this study offers a robust framework for simulating and analysing the complex interactions within the tobacco retail market, and may provide a valuable insight for policymakers.

6.2 Limitations

Despite successfully implementing complex agent interactions and a realistic environment, this study still has several limitations. These mainly result in the data quality and model design.

For the data aspect, the model's accuracy relies on the quality and completeness of data sources. Dependence on official sales data and survey-based smoking statistics introduces potential biases, particularly under-reporting in surveys, which may cause error between the model's validation output and actual figures, potentially ranging from 5% to 10%. While this does not fundamentally alter conclusions, it affects the initial data generation.

Additionally, the model incorporates data from various years, primarily 2022, but older data was also used due to the lack of recent data, potentially influencing accuracy when researching current trends. Some logical errors might arise due to randomness in attribute generation, such as costs being higher than prices, which are corrected by adjusting the related attributes randomly. Though this occurs in less than 0.05% of cases, it still affects accuracy due to the small scale of the agent group.

For model design, certain consumer and retailer behaviors are simplified. For instance, periodic re-selection of preferred retailers by agents may not fully capture real-world decision-making, and rapid strategy changes by retailers may oversimplify market dynamics. The initial location assignments for agents also lack specific clustering, such as residential or commercial areas, which could impact simulation outcomes. Lastly, the model doesn't account for broader economic or social factors, which could lead to different outcomes and may require further refinement to enhance predictive power.

6.3 Future Works

Future research should focus on both addressing these limitations and exploring additional directions to enhance the model's accuracy and applicability. To reduce biases, more up-to-date and comprehensive data sources, including time-unified and detailed agent distribution data, should be integrated.

Refining the model's logic to better handle random errors and more accurately reflect consumer and retailer behaviors—such as introducing randomised decision-making periods and refining location assignments—would improve the reliability and realism of the simulation. Expanding the model to incorporate broader economic and social factors could also enhance its predictive power and relevance for policymakers.

Further research could optimise the ABM by integrating more complex algorithms to better simulate strategic behaviors and location choices of large retailers, especially in response to policy changes. Applying the model in real-world settings, such as specific cities or regions, could provide practical insights through pilot programs. Incorporating more detailed behavioral factors for adult agents, such as addiction severity and health awareness, would deepen the understanding of responses to tobacco control measures. Finally, exploring interactions between multiple tobacco control policies could identify the most effective combinations, maximising public health benefits while minimising economic disruptions—an intriguing direction for future work.

Bibliography

[1] World Health Organization. Who report on the global tobacco epidemic 2021: addressing new and emerging products, 2021. Accessed: 2024-08-18.

[2] Scottish Government. Tobacco and vaping framework: A roadmap to 2034, 2021. Accessed: 2024-08-18.

[3] Jacqueline A Bowden, Joanne Dono, David L John, and Caroline L Miller. What happens when the price of a tobacco retailer licence increases? *Tobacco Control*, 23(2):178–180, 2014.

[4] Eric Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, 99(suppl_3):7280–7287, 2002.

[5] Shubing Guo, Junhai Ma, Xueli Zhan, et al. Complexity and application of tobacco manufacturer pricing game considering market segments. *Discrete Dynamics in Nature and Society*, 2017, 2017.

[6] Joseph GL Lee, Amanda Y Kong, Kerry B Sewell, Shelley D Golden, Todd B Combs, Kurt M Ribisl, and Lisa Henriksen. Associations of tobacco retailer density and proximity with adult tobacco use behaviours and health outcomes: a meta-analysis. *Tobacco control*, 31(e2):e189–e200, 2022.

[7] Todd B Combs, Virginia R McKay, Joseph Ornstein, Margaret Mahoney, Kerry Cork, Deena Brosi, Matt Kasman, Benjamin Heuberger, Ross A Hammond, and Douglas Luke. Modelling the impact of menthol sales restrictions and retailer density reduction policies: insights from tobacco town minnesota. *Tobacco control*, 29(5):502–509, 2020.

[8] Lindsay Robertson and Louise Marsh. Estimating the effect of a potential policy to restrict tobacco retail availability in new zealand. *Tobacco control*, 28(4):466–468, 2019.

[9] Anna B Gilmore, Behrooz Tavakoly, Gordon Taylor, and Howard Reed. Understanding tobacco industry pricing strategy and whether it undermines tobacco tax policy: the example of the uk cigarette market. *Addiction*, 108(7):1317–1326, 2013.

[10] Colleen Smyth, Becky Freeman, and Audrey Maag. Tobacco retail regulation: the next frontier in tobacco control. *Public Health Res Pract*, 25(3):e2531529, 2015.

[11] Mirte AG Kuipers, Paulien AW Nuyts, Marc C Willemsen, and Anton E Kunst. Tobacco retail licencing systems in europe, 2022.

[12] Roberto Valiente, Helena Tunstall, Amanda Y Kong, Luke B Wilson, Duncan Gillespie, Colin Angus, Alan Brennan, Niamh K Shortt, and Jamie Pearce. Geographical differences in the financial impacts of different forms of tobacco licence fees on small retailers in scotland. *Tobacco Control*, 2024.

[13] Mark Taylor, Vince Kwasnica, Denis Reilly, and Somasundaram Ravindran. Game theory modelling of retail marketing discount strategies. *Marketing Intelligence & Planning*, 37(5):555–566, 2019.

[14] Praveen K. Kopalle and Robert A. Shumsky. 381 Game Theory Models of Pricing. In *The Oxford Handbook of Pricing Management*. Oxford University Press, 06 2012.

[15] Shari P Feirman, Allison M Glasser, Shyanika Rose, Ray Niaura, David B Abrams, Lyubov Teplitskaya, and Andrea C Villanti. Computational models used to assess us tobacco control policies. *Nicotine & Tobacco Research*, 19(11):1257–1267, 2017.

[16] Ross A Hammond. Considerations and best practices in agent-based modeling to inform policy. In *Assessing the use of agent-based models for tobacco regulation*. National Academies Press (US), 2015.

[17] Douglas A Luke and Katherine A Stamatakis. Systems science methods in public health: dynamics, networks, and agents. *Annual review of public health*, 33(1):357–376, 2012.

[18] Robert B Wallace, Amy B Geller, V Ayano Ogawa, et al. *Assessing the use of agent-based models for tobacco regulation*. National Academies Press Washington, DC, 2015.

[19] Jack B Homer and Gary B Hirsch. System dynamics modeling for public health: background and opportunities. *American journal of public health*, 96(3):452–458, 2006.

[20] Douglas A Luke, Ross A Hammond, Todd Combs, Amy Sorg, Matt Kasman, Austen Mack-Crane, Kurt M Ribisl, and Lisa Henriksen. Tobacco town: computational modeling of policy options to reduce tobacco retailer density. *American journal of public health*, 107(5):740–746, 2017.

[21] Charles M Macal and Michael J North. Tutorial on agent-based modeling and simulation. In *Proceedings of the Winter Simulation Conference, 2005.*, pages 14–pp. IEEE, 2005.

[22] Fiona Caryl, Niamh K Shortt, Jamie Pearce, Garth Reid, and Richard Mitchell. Socioeconomic inequalities in children's exposure to tobacco retailing based on individual-level gps data in scotland. *Tobacco Control*, 29(4):367–373, 2020.

[23] Fiona M Caryl, Jamie Pearce, Garth Reid, Richard Mitchell, and Niamh K Shortt. Simulating the density reduction and equity impact of potential tobacco retail control policies. *Tobacco control*, 30(e2):e138–e143, 2021.

[24] Scottish Government. Scottish health survey. `https://www.gov.scot/collections/scottish-health-survey/`, 2022. Accessed: 2024-02-07.

[25] Scottish Government. Scottish index of multiple deprivation 2020. `https://www.gov.scot/collections/scottish-index-of-multiple-deprivation-2020/`, 2020. Accessed: 2024-02-07.

[26] National Records of Scotland. Scotland's census 2022 rounded population estimates data. `https://www.scotlandscensus.gov.uk/documents/scotland-s-census-2022-rounded-population-estimates-data/`, 2022. Accessed: 2024-02-07.

[27] National Records of Scotland. Population estimates by urban rural classification. `https://www.nrscotland.gov.uk/statistics-and-data/`

statistics/statistics-by-theme/population/population-estimates/2011-based-special-area-population-estimates/population-estimates-by-urban-rural-classification, 2011. Accessed: 2024-02-07.

[28] ASH Scotland. The effect of smoking on personal finances and poverty in scotland, 2024. Accessed: 2024-08-25.

[29] J Bradford De Long, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann. Noise trader risk in financial markets. *Journal of political Economy*, 98(4):703–738, 1990.

[30] Patricia A McDaniel, Elizabeth A Smith, and Ruth E Malone. Retailer experiences with tobacco sales bans: lessons from two early adopter jurisdictions. *Tobacco Control*, 2023.

[31] Herbert L Lyon and Julian L Simon. Price elasticity of the demand for cigarettes in the united states. *American Journal of Agricultural Economics*, 50(4):888–895, 1968.

[32] Sam Cameron. Estimation of the demand for cigarettes: a review of the literature. *ECONOMIC ISSUES-STOKE ON TRENT-*, 3:51–72, 1998.

[33] Drew Fudenberg and Jean Tirole. *Game theory*. MIT press, 1991.

[34] Abolfazl Kazemi and Zohreh SaeedMohammadi. A model for cooperative advertising and pricing decisions in manufacturer-retailer supply chain with discount: a game theory approach. *International Journal of Supply and Operations Management*, 2(4):1035–1063, 2016.

[35] Steffen Jørgensen and Georges Zaccour. A differential game of retailer promotions. *Automatica*, 39(7):1145–1155, 2003.

[36] Fahri Karakaya. Market exit and barriers to exit: Theory and practice. *Psychology & Marketing*, 17(8):651–668, 2000.

[37] René Caldentey, Ying Liu, and Ilan Lobel. Intertemporal pricing under minimax regret. *Operations Research*, 65(1):104–129, 2017.

[38] Patrick L Anderson, Richard D McLellan, Joseph P Overton, and Gary L Wolfram. Price elasticity of demand. *McKinac Center for Public Policy. Accessed October*, 13(2), 1997.

[39] Pradeep K Chintagunta, Andre Bonfrer, and Inseong Song. Investigating the effects of store-brand introduction on retailer demand and pricing behavior. *Management Science*, 48(10):1242–1267, 2002.

[40] Ver Bilano, Stuart Gilmour, Trevor Moffiet, Edouard Tursan d'Espaignet, Gretchen A. Stevens, Alison Commar, Frank Tuyl, Irene Hudson, and Kenji Shibuya. Global trends and projections for tobacco use, 1990-2025: an analysis of smoking indicators from the WHO comprehensive information systems for tobacco control. *The Lancet*, 385(9972):966–976, 2015.

[41] Adarsh Prabhakaran, Valerio Restocchi, and Benjamin D Goddard. Improving tobacco social contagion models using agent-based simulations on networks. *Applied Network Science*, 8(1):54, 2023.

[42] Nicholas A Christakis and James H Fowler. The collective dynamics of smoking in a large social network. *New England journal of medicine*, 358(21):2249–2258, 2008.

[43] National Records of Scotland. Population estimates by urban rural classification. `https://www.nrscotland.gov.uk/statistics-and-data/statistics/statistics-by-theme/population/population-estimates/2011-based-special-area-population-estimates/population-estimates-by-urban-rural-classification`, 2024. Accessed: 2024-08-11.

[44] Scottish Government. Poverty in rural scotland. `https://www.gov.scot/publications/poverty-rural-scotland-review-evidence/pages/4/`, 2024. Accessed: 2024-08-11.

[45] Nick Bailey, Glen Bramley, and Maria Gannon. Poverty and social exclusion in urban and rural areas of scotland. 2016.