Agent-Based Modeling of Retailer Tobacco Licensing Fees: Assessing Socioeconomic Impacts on Smokers

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Abstract

The project was undertaken to explore how tobacco retailer licensing fees could influence smoking prevalence, particularly in the context of economic disparities in Scotland. Smoking remains a significant public health challenge, making it crucial to evaluate the effectiveness of various policy interventions to design strategies that equitably reduce smoking rates across different socioeconomic groups. The decision to focus on this issue stems from ongoing public health discussions about the most effective methods to curtail smoking, particularly in economically disadvantaged communities, where smoking rates are typically higher and more resistant to change.

The research utilized an agent-based modelling (ABM) approach to create a virtual environment representing various town types, allowing for the simulation of the potential impact of three distinct licensing fee structures—volumetric, universal, and urban-rural—on smoking behaviours. This approach was applied to different town types, including urban, rural, most deprived, and least deprived areas. The ABM framework enabled a nuanced examination of how financial constraints and social peer interactions might influence changes in smoking habits under various policy scenarios. Integrating network structures into the ABM model was particularly crucial, offering a unique perspective on the effects of peer influence on smoking behaviour and adding a layer of complexity to the simulation.

While the specific results highlighted the varying effectiveness of each fee structure in different contexts, the broader takeaway emphasizes the importance of a differentiated policy approach. The findings suggest that a one-size-fits-all solution may not be effective, and tailored strategies, such as the urban-rural fee scheme, could more effectively balance reducing smoking prevalence with minimizing socioeconomic disparities.

Overall, the project underscores the necessity of targeted policy interventions that address the diverse needs of different communities, offering a valuable framework for future public health strategies aimed at reducing smoking rates across Scotland.

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.

(*Dharmavenkatesan Kadhappullapatty Balakrishnan*)

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Chapter 1

Introduction

1.1 Introduction

The main objective of this dissertation is to evaluate the impact of introducing retailer licensing fees on smoking behaviour across different socioeconomic classes in Scotland. This research seeks to determine whether such a policy effectively reduces smoking prevalence nationwide, particularly in terms of its effects on socioeconomic disparities. In the context of public health in Scotland, various measures and laws have been implemented or are under review to curb smoking rates. One such measure under consideration is the introduction of retailer licensing fees for tobacco products. Understanding the potential positive and negative effects of this policy, especially across different socioeconomic classes, is crucial for informing effective and equitable policymaking.

1.2 Background

Tobacco use remains one of the leading causes of preventable disease and death worldwide. In Scotland, significant efforts have been made to reduce smoking rates through various public health initiatives. These include smoking cessation programs, public smoking bans, increased taxation on tobacco products, and educational campaigns highlighting the risks of smoking.

Despite these efforts, smoking prevalence remains higher among lower socioeconomic groups, contributing to health disparities[5]. Previous research has shown that socioeconomic factors such as income, education, and residential area (urban vs. rural) influence smoking behaviours and responsiveness to public health interventions.

The introduction of retailer licensing fees is a relatively new approach aimed at regulating the sale of tobacco products. This policy requires retailers to obtain a licence to sell tobacco, potentially reducing the number of outlets where tobacco products are available. The rationale behind this measure is that by limiting accessibility, smoking rates may decrease, particularly among vulnerable populations. However, the differential impact of such a policy on various socioeconomic classes has not been thoroughly investigated.

1.3 Motivation

The primary motivation behind this study is to address the need for effective public health policies that reduce smoking prevalence in Scotland, with a specific focus on understanding the differential impacts on various socioeconomic groups. The introduction of retailer licensing fees represents a significant policy intervention aimed at achieving this goal. However, the impact of such a measure on different socioeconomic groups, including variations based on income levels and residential areas (urban vs. rural), remains unclear. This research aims to fill that gap by examining how different socioeconomic groups respond to the introduction of retailer licensing fees.

Given the complexity of this issue, technological advancements offer a valuable tool for modelling and simulating the potential outcomes of such policies. Agent-based modelling (ABM) allows for the simulation of complex social systems and interactions. This dissertation will utilize ABM to design and simulate the environment in Scotland, assessing how the introduction of retailer licensing fees might affect various socioeconomic groups of smokers. The goal is to provide insights into the potential effects of this policy on different socioeconomic classes, informing future public policy strategies and interventions.

This dissertation is structured as follows: Chapter 2 reviews the relevant literature, Chapter 3 outlines the research methodology and model design, Chapter 4 presents results and analysis, and Chapter 5 discusses the conclusions and recommendations.

Chapter 2

Literature Review

This literature review is divided into four parts. The first part aims to understand the issue of smoking. The second part explores the feasibility of retailer fees. The third part examines the socioeconomic issues associated with this policy. Lastly, it provides a literary background on agent-based models (ABMs) and their applications in policy-making.

2.1 Smoking

Smoking remains a significant public health concern worldwide, contributing to a variety of serious illnesses, including cancer, heart disease, stroke, lung diseases, and diabetes[10]. In Scotland, the fight against smoking is crucial not only for public health but also for economic reasons. According to a 2024 fact sheet by ASH Scotland, the cost of smoking-related illnesses to the National Health Service (NHS) in Scotland can range between £300 million and £500 million annually [6]. This staggering figure represents a significant burden, consuming a substantial portion of Scotland's healthcare budget.

Recognizing the significant health and economic burden of smoking, the Scottish Government has implemented proactive measures to decrease smoking prevalence and prevent new smokers from starting. The United Kingdom implemented a comprehensive ban on smoking in enclosed public places in 2006, with Scotland leading the way [30]. The minimum legal age for tobacco purchase in the United Kingdom was raised from 16 to 18 years in 2007, applying consistently across England, Wales, and Scotland [12]. Scottish government strategy, "Creating a tobacco-free generation: A Tobacco Control Strategy for Scotland" launched in 2013, outlines a comprehensive plan to achieve a smoke-free generation, defined as less than 5% of all adults smoking [16]. This plan includes initiatives such as stricter smoking bans in public spaces, public awareness campaigns about the dangers of smoking, and the provision of smoking cessation services.

Because of these measures, smoking rates in Scotland have demonstrably decreased. Statistics show a decline in adult smoking prevalence, with 11% of adults reported as smokers in 2021 compared to 28% in 2003 [34]. However, significant public health concerns remain, indicating that there is still room for improvement. One intriguing approach that has been studied worldwide is the implementation of retailer licensing fees.

2.2 Licensing Fees

The framework for implementing licensing systems to regulate product availability and access has been explored worldwide. Different regions have experimented with tobacco licensing, requiring retailers to obtain special authorization to legally sell tobacco products. This strategy is considered crucial for effective tobacco control. Licensing may enhance smoking prevention by improving the enforcement of tobacco control policies, reducing the number of retail outlets, and demoralizing tobacco use[22]. The effectiveness of these systems depends on the costs and criteria for obtaining licenses, such as minimum distances from schools or other retailers.

Licensing schemes for tobacco retailers have been widely studied and shown to be effective in reducing tobacco availability and consumption. The researchers examined the implementation of retailer licensing systems in Europe, highlighting various outcomes and best practices that can inform policy design [7]. Licensing restrictions often lead to a reduction in the number of retailers, which, as documented in studies, correlates with decreased smoking prevalence [19].

Point-of-sale promotion restrictions and well-funded compliance programs to prevent sales to minors, combined with retailer licensing, education, and enforcement, have the potential to further denormalize tobacco smoking and reduce its prevalence[35].In New South Wales (NSW), current tobacco retailer laws generally align with the evidence, with high overall compliance observed. Australia has achieved significant reductions in smoking rates, prompting public health initiatives to focus on additional measures such as licensing to manage retailer density and proximity to sensitive locations[35].

The introduction of retailer fees for tobacco sales is likely to have both direct and indirect effects on businesses. These fees will increase retailers' costs, potentially leading them to either raise prices for consumers or absorb the cost and potentially suffer reduced profits. In the latter case, shop closures could occur, leading to a decrease in retail density. This reduction in tobacco outlets has been linked to lower smoking prevalence, as evidenced by research conducted by NHS Scotland [23] which found a correlation between lower retailer density and reduced smoking rate

The existence of a well-established tobacco retailer registration system in Scotland, as documented by the Scottish Tobacco Retailers Register[2], demonstrates the feasibility of implementing a licensing scheme. This existing infrastructure, which already functions as a database of retailers, simplifies the process of transitioning to a licensing system.

2.3 Socioeconomic Disparity

Socioeconomic inequalities in smoking are major contributors to health disparities in high-income countries. In UK populations, studies show that a significant portion of social inequalities in adult male mortality is attributable to smoking. Widespread cessation of smoking has the potential to halve the absolute differences in premature death risk between these social strata [21].

In Scotland, these trends are reflected in local smoking behaviours and health outcomes. Studies consistently show a higher prevalence of smoking among socioeconomically disadvantaged groups within Scotland, paralleling international findings. Usher Institute, reports that in Scotland, smoking prevalence among those living in the most deprived areas is a staggering 35%, compared to just 10% in the least deprived areas [27]). The financial strain of smoking further exacerbates economic inequality. According to ASH Scotland, a household in the lowest income bracket with a smoker can spend nearly 30% of their disposable income on cigarettes[6]

Approximately 63,000 households in Scotland would no longer experience relative poverty if individuals were empowered to successfully quit tobacco. The analysis also shows that 42% of all households in Scotland containing people who smoke live in relative poverty, and there would be around 10% fewer in those circumstances if tobacco was out of their lives. Reducing smoking prevalence in Scotland by just one per cent could lift more than 3,700 households out of relative poverty[5].

Research has shown that Policies that are targeted may be highly effective in preventing and reducing socioeconomic inequalities in youth smoking initiation [4].

Given the disparities present in Scotland, as evidenced by data, any further policy must avoid a one-size-fits-all approach. Literature and research evidence supports the need for a cautious approach, suggesting that more research should be conducted to develop policies that address the unique circumstances of different populations.

2.4 Agent Based modelling(ABM)

Design and implementation of policies, especially public policies such as tobacco control, have traditionally relied on statistical methods or natural observations. However, the last decade has seen an increase in the use of computational modelling approaches as a complement to traditional policy designs.

Computational modelling is particularly useful for addressing complex systems, such as those involving tobacco products. Smoking habits and purchase decisions, including initiation, consumption, and cessation, result from a complex interplay of factors like peer influence, product availability, pricing, and various other dynamics. The use of computational modelling in complex systems offers ample opportunities to evaluate various policy interventions across different populations and time frames [17]. It also enables the capture of interactions resulting from these interventions and their effects on people, which is challenging, if not impossible, to address through traditional experimental or observational policy designs[25]. This approach also enhances the ability to consider the multifaceted nature of policy measures. Computational systems modelling is a powerful research tool for public health policies, especially when traditional experimental and observational studies of retail policies are not possible or practical [18].

Agent-based modelling is a type of dynamic computational modelling that uses computer simulations to examine how elements of a system (agents) behave as a function of their interactions with each other and their environment[25]. It examines how individual elements (agents) within a system behave based on their individual characteristics, interactions with each other, and their environment. Each agent follows a set of rules and interacts within a specified environment, resulting in specific outcomes, some of which may be unexpected. ABMs are valuable for exploring the potential effects of policies and interventions in dynamic social and physical environments[20]. Agent-based modelling (ABM) is effective for examining interactions between individual behaviour and the evolving environmental and social contexts (Bruch et al., 2015). ABM's focus on agent interactions enables a detailed exploration of how public policies impact individual behaviour, as well as how local physical and social environments influence behavioural dynamics. Additionally, ABM can serve as a proxy to observe aggregate statistics, illustrating how individual behaviours contribute to larger population dynamics. As such, ABMs can serve as useful tools to inform decision-making by policymakers.

Agent-based modelling (ABM) has been acknowledged as a valuable tool in tobacco regulatory studies, yet its full potential remains largely untapped [13] Recently, there has been a growing recommendation to utilize agent-based models more extensively for studying policy mechanisms and their impacts in tobacco control [20]

While this literature review has explored the general health impacts of policies like retailer fees across socio-economic groups, a significant knowledge gap exists regarding their specific impacts on marginalised communities in Scotland. Existing literature highlights socio-economic disparities in smoking prevalence, but fails to address how specific policies, like new licensing fee schemes, might interact with and potentially exacerbate these inequalities. This lack of understanding hinders the development of effective tobacco control strategies.

This research aims to address two critical gaps. First, it tackles the knowledge gap in the literature regarding the specific impact of policies like retailer fees on marginalised communities in Scotland. Existing research highlights socio-economic disparities in smoking prevalence, but fails to address how specific policies interact with these inequalities. Second, this research aims to fill a research gap by specifically examining the impact of retailer fees on different socio-economic classes of smokers in Scotland.

This also aligns with the broader agenda of precision prevention, which aims to tailor evidence-based strategies to specific contexts to enhance effectiveness, avoid unintentional consequences, and promote sustainable policy implementation. This approach was suggested by Hammond et al.[17], who emphasized the importance of context-specific strategies.

Chapter 3

Design and Method

3.1 Networks

In agent-based modelling, incorporating a network structure is crucial for accurately simulating the interactions and behaviours of agents. Network structures allow for the representation of complex social interactions and influence patterns, enabling agents to interact with a specific set of other agents (neighbours), reflecting real-world social connections. This is essential for understanding behaviours such as smoking cessation, as individuals are more likely to be affected by the behaviours and attitudes of those they are directly connected to. In real life, smokers are often influenced to quit by their social networks, and this dynamic is reflected in the model via a network structure.

In the context of smoking cessation, this means understanding how quitting behaviour can propagate through social networks, influenced by friends, family, and peers who have quit smoking themselves. Networks naturally incorporate heterogeneity and clustering within populations. Different agents can have varying numbers of connections (degree), and clusters of highly interconnected agents can form. This mirrors real social networks where certain groups may be more tightly knit, influencing each other more strongly.

Compared to models without network structures, network-based models offer a more nuanced and accurate depiction of social influence. Models lacking network structures often assume that each agent is independent of others, and their decisions have no impact on each other. This is not reflective of real-world environments, where social connections and peer influences play a significant role. This oversimplification can lead to inaccurate predictions and an inability to capture localized effects and the true dynamics of behaviour change.

Modelling these interactions through networks captures the subtleties of peer influence, social pressure, and the spread of behaviours within a community. This approach is significantly more realistic and informative compared to models without network structures, where interactions are often oversimplified or entirely absent.

3.1.1 Network Structure

Small-world networks, as described by Watts and Strogatz [37], are characterized by high clustering and short average path lengths, making them particularly suitable for modelling social networks where individuals are influenced by their close neighbours but can also be affected occasionally by distant connections. This mirrors real-world social interactions where smoking behaviour and cessation are influenced by peer groups and broader social influences. The high clustering effectively captures the tightly-knit groups found in real social networks, crucial for simulating smoking cessation influenced by close social ties. Short average path lengths ensure that behaviours and information can spread across the network, reflecting broader social connections beyond immediate peer groups. The small-world network structure balances local interactions and global connectivity, essential for accurately modelling social phenomena like smoking cessation. An average degree of 4 was chosen based on empirical data from existing social network studies [29], indicating that individuals typically maintain a moderate number of social connections. The network is bidirectional, meaning that the relationship between nodes is mutual. If node A is a neighbour of node B, then node B is also considered a neighbour of node A. This bidirectional nature ensures that connections within the network are reciprocal, reflecting a symmetric relationship where the influence or interaction between two nodes flows both ways, rather than being one-sided.

3.1.2 Degree Distribution

The degree distribution of the network is verified to ensure that the small-world properties are maintained. The degree distribution of the four types of agents is illustrated in the below Figure from the base model. The degree counts are analysed and plotted, showing the distribution of connections among agents. The resulting distribution follows a Poisson distribution, which is the expected outcome for a small-world network. This analysis confirms the network's suitability for simulating social interactions related to smoking cessation.

The network was constructed with an average degree of 4, which is characteristic of small-world networks with high clustering and short path lengths. This design reflects the findings of Christakis and Fowler [11], who emphasize that the spread of smoking behaviour primarily occurs within close-knit groups of family members and friends. Consequently, the number of individuals who can potentially influence smoking behaviour is lower than what would be expected in a broader social network. This intimate network structure is crucial in shaping the dynamics of smoking initiation and cessation, supporting the decision to construct a network with a smaller average degree. By modelling a network with these characteristics, the simulation more accurately reflects the real-world social influences on smoking behaviour.

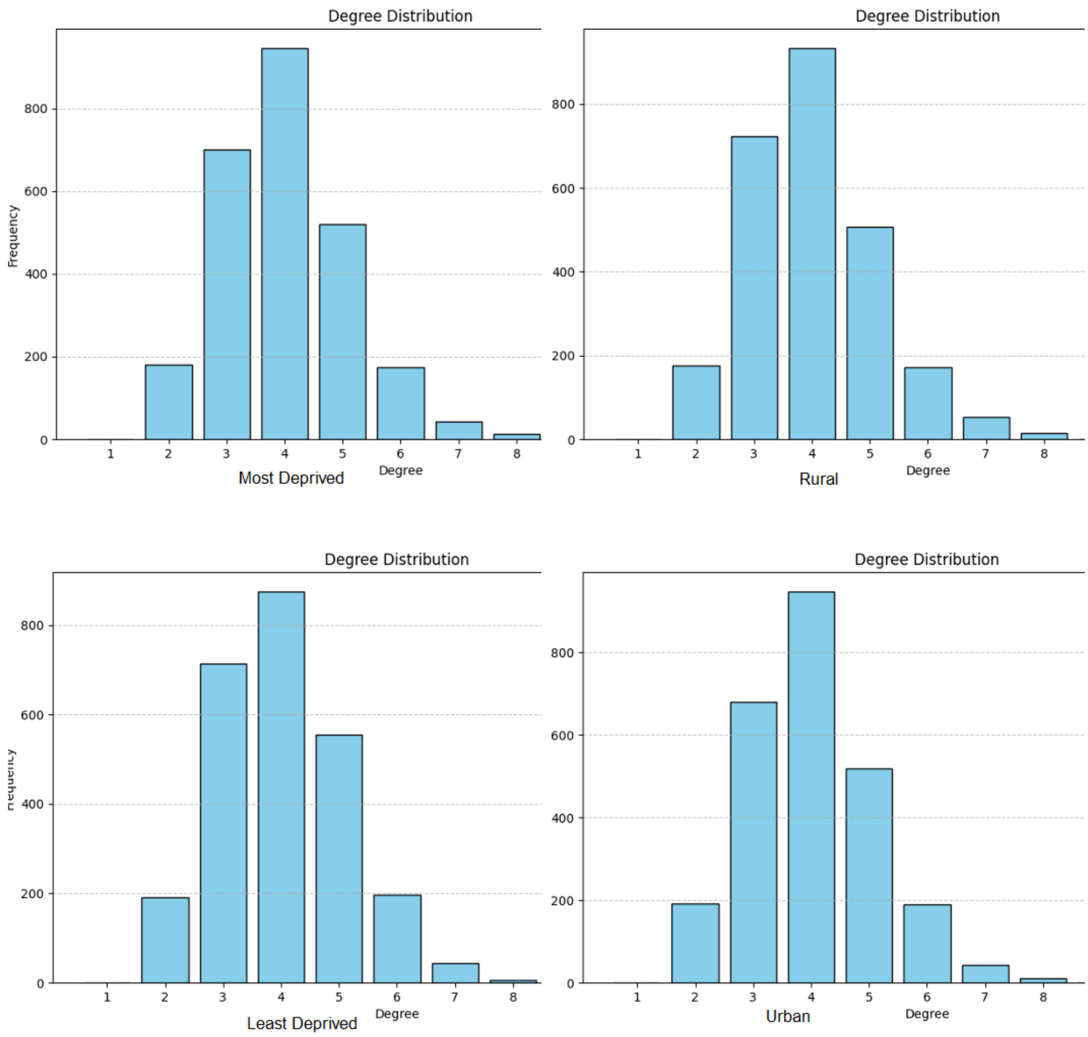

Figure 3.1: Degree Distribution for all Town types from Base Model

To validate the network, the degree distribution was carefully analysed. This analysis confirms that the network maintains the essential small-world properties needed to accurately simulate social interactions. The observed degree distribution, showing a Poisson-like spread, verifies the network's suitability.

The network involved in the spread of smoking behaviour primarily comprises close family members and friends, as highlighted by Christakis and Fowler[11]. Consequently, the number of individuals who can potentially influence smoking behaviour is likely to be lower than the average degree observed in a standard social network. This more intimate network structure implies that the dynamics of smoking initiation and cessation are shaped by a smaller, more closely-knit group of influencers, rather than a broader social network.

The model simulates the network over a fixed period, updating agents' statuses and recording the transitions from smokers to quitters. This one-time update at the end of every year ensures that there is no indefinite transition period and provides a clear snapshot of smoking cessation dynamics. The network's structure allows for the observation of how smoking cessation spreads through social interactions.

The incorporation of a small-world network into the agent-based model provides a realistic framework for studying smoking cessation dynamics. This network structure effectively captures the social influences on smoking behaviour among individuals aged 34–45. By employing parameters and probabilistic rules that mirror real-world social interactions, the model ensures that the simulated behaviours are both realistic and insightful. By integrating this validated small-world network, the model can simulate how quitting behaviour propagates through social networks, providing valuable insights into the dynamics of smoking cessation and the impact of social influences.

3.1.3 Smoking Cessation

In the model, each agent can be in one of the following smoking states: never-smoker (N), smoker (S), or quitter (Q). An agent is classified as a never-smoker if they have never smoked before, while an agent who smokes any tobacco product daily or occasionally is categorized as a smoker. If a smoker quits smoking, even temporarily, they are labelled a quitter. Agents are initially assigned to these states based on existing survey data. The process of an S-agent quitting smoking is referred to as smoking cessation, which can occur through two primary mechanisms. First, external influences such as mass-media campaigns, mandatory warning labels on cigarette boxes, and higher taxes are incorporated into the model through a spontaneous cessation term. Second, cessation can occur due to interactions with non-smokers, which include both Q-agents and N-agents. Thus, interactions with either state can lead to smoking cessation. The probability of cessation for an S-agent due to N-agents in its network neighbourhood is represented by $P(S \to Q \mid N)$, while the probability of cessation due to Q-agents is represented by $P(S \to Q \mid Q)$.

To account for the impact of multiple independent interactions on an agent's behaviour, it's assumed that each exposure to an agent with a different smoking status is independent of previous exposures. To calculate the probability of a state change in such cases, a binomial approximation is used. This approach compounds the effects of multiple simultaneous independent interactions, providing a more accurate estimation of the likelihood of an agent transitioning between states based on their network interactions.

In the model, consider an agent i with state Z, who has n_i neighbours, of which $n_{Y,i}$ are in state Y. When agent i interacts with a Y neighbour, the interaction can result in two outcomes: success, where agent i transitions to state Y, or failure, where agent i remains in state Z. Let b denote the probability of a successful interaction with a Y agent, and k represent the number of successful interactions. The probability of k successes is given by the binomial distribution:

binomial expression

$$P(k) = \binom{n}{k} b^k (1-b)^{n-k}$$

To determine the probability of a state change, the calculation focuses on the probability of achieving at least one success:

$$P = P(k > 0) = 1 - P(k = 0) = 1 - (1-b)^{n_i}$$

This calculation focuses solely on the number of agents, without accounting for the total number of neighbors. However, research indicates that the proportion of agents within an individual's social circle, rather than the absolute number, significantly influences smoking behaviour. To account for the size of the network and the relative presence of neighbours, the probability of state change is scaled by the fraction of neighbours among the total neighbours of agent i.

The probability of a smoker agent i quitting due to interaction with quitters is:

$$P(S \to Q \mid Q) = \frac{n_{Q,i}}{n} \left(1 - (1-g)^{n_{Q,i}}\right)$$

where:

- n is the total number of neighbors of the smoker agent i.
- $n_{Q,i}$ is the number of neighbors who are quitters.
- g is the probability of quitting per interaction with a quitter.

The probability of a smoker agent i quitting due to interaction with never-smokers is:

$$P(S \to Q \mid N) = \frac{n_{N,i}}{n}\left(1 - (1-d)^{n_{N,i}}\right)$$

where:

- n is the total number of neighbors of the smoker agent i.
- $n_{N,i}$ is the number of neighbors who are never-smokers.
- d is the probability of quitting per interaction with a never-smoker.

An empirical approach was adopted to determine the interaction parameters for the model, drawing on established research in the field. One key reference was a paper focused on improving social contagion through agent-based simulation models. This paper provided valuable insights into interaction parameters within various types of networks, including small-world networks, which align with the structure used in the model.

For the interaction parameters, particularly the parameters g and d, the values are derived from the paper[29].

The aforementioned model relies on the findings from both the Framingham Heart Study (FHS) and the work by Christakis et al. [11] to determine the interaction parameter g, which represents smoking cessation due to interactions with smokers. These studies provide the basis for both the interaction parameters and the spontaneous cessation parameters, using the formulas and values derived directly from the research.

The average probability from the seventh wave of FHS data was utilized, with the calculated value for smoking cessation due to social interactions being g'=0.35214 [11]. This value serves as a crucial parameter for simulating the impact of social networks on smoking cessation within the modelled population.

The integration of this parameter into the model involved calculating the interaction probability per year using the following formula:

$$g = 1 - (1 - g'\left(1 - (1 - \delta_{S \to Q})^t\right)^t$$

where $\delta_{S \to Q} = 0.02$, which represents the spontaneous smoking cessation rate.

The parameter d, representing the probability of quitting smoking per interaction with a non-smoker, was empirically determined from the paper, with a value of 0.02. This parameter quantifies the effect of social interactions with non-smokers on smoking cessation, allowing the model to account for the influence of such interactions on an individual's likelihood of quitting smoking

3.2 Policy and Simulation Conditions

When defining policies and running simulations, it is important to understand the implications from both a policy perspective and a retailer's perspective. Across Europe, including in Scotland, two policy schemes have been widely implemented or considered for smoking cessation[22]: the universal scheme and the volumetric scheme. Both play critical roles in shaping the effectiveness of smoking cessation efforts.

3.2.1 Policy

In this model, both the universal scheme and the volumetric scheme are employed. The universal scheme applies a consistent policy across all agents, ensuring uniformity in regulatory impact, while the volumetric scheme targets agents based on the number of cigarettes sold, reflecting real-world approaches where policies are designed to influence consumption volumes.

Initially, a pure volume-based volumetric fee structure was considered, where the fee was calculated based on a specific number of sticks (e.g., 1,000 sticks) sold. After running the simulations under this policy, it was observed that the impact on smoking prevalence was minimal. This outcome occurred because the price increase for each pack of cigarettes was directly linked to the retailer's sales volume. Retailers, therefore, adjusted their prices proportionately to their sales volumes, leading to a situation where the price increase was not substantial enough to discourage smokers from continuing their habit.

As a result, the intended effect of reducing smoking prevalence was not achieved, as the financial disincentive was insufficient to motivate smokers to quit. The results of this initial pure volumetric fee structure are documented in Appendix A.4.

To address this issue, an alternative volumetric fee structure was explored, where a base volumetric fee was set, plus an additional fee based on the retailer's sales volume.

This modified volumetric fee structure was used throughout the model, as it provided a more effective balance by ensuring that the price increase was significant enough to influence smokers' behaviour. The rationale behind this adjustment was to create a stronger financial deterrent for smoking, which was more likely to lead to a reduction in smoking prevalence

Additionally, a third policy scheme was explored, focusing on urban-rural differentiation. This scheme recognizes the distinct economic conditions, social dynamics, and access to resources that vary between urban and rural areas. In urban regions, where population density and access to retailers are typically higher, policies might be designed to address the more intense commercial activity and potentially greater exposure to smoking influences. Conversely, rural areas, which often have lower population density and fewer retail outlets, might require different strategies that account for longer travel distances to retailers and different social norms around smoking. This urban-rural differentiated approach aims to evaluate whether tailoring policies to these unique conditions could lead to more effective smoking cessation outcomes.

In the fee-based policy simulations, the decision to test fees without increments was driven by several considerations. Firstly, a fixed fee simplifies the model, offering a clear baseline for assessing the impact of licencing fees. This approach allows for a straightforward evaluation of how a single fee level influences retailer behaviour and smoking cessation without the added complexity of dynamic fee adjustments. Additionally, implementing a fixed fee mirrors real-world policy practices, where policymakers might initially introduce a static fee to gauge its effects before considering incremental changes.

Structure	**Fees/Year**
Universal Fee (£)	4,757.66
Volumetric Fee (£/1000 sticks sold)	Base Fee= 1,824 ; Volume = 9.97/1000 sticks
Urban/Rural Fee (£)	Urban = 5,474.21 ; Rural = 2,291.36

Table 3.1: Fee Structures. Detailed calculations are available in Appendix A.2

In total, three policy schemes were finalised and tested within the model to provide a comprehensive analysis of their potential impacts on smoking behaviour and retail operations. This allows for a nuanced understanding of how different policy frameworks might influence smoking cessation across diverse populations and geographical areas

The fee structures for the three types of scenarios were established based on a combination of literature evidence, guidance from the project supervisor, and insights from experts who have been conducting research on these policies over an extended period. These experts, who have been instrumental in shaping the fee structures, are acknowledged in the report's acknowledgement section. The design of these fee structures is detailed in the following table, which outlines the specific parameter

3.2.2 Retailer Response:

When a licensing fee is introduced, retailers face several possible actions in response, such as absorbing the fee, passing it on to consumers, or partially closing stores. Given the range of choices and the complexity involved, it was decided to focus on the two most common and straightforward actions in the model. These are: either the retailer fully passes the fee onto consumers, meaning that the price increase is entirely borne by the customers, or the retailer decides to shut down the store.

These two responses—passing the fees onto consumers or closing the store—were chosen because they represent the most straightforward and realistic outcomes in a retail environment when faced with increased operational costs due to licensing fees.

Passing the Fee onto Consumers: This option is a common strategy used by retailers to maintain profit margins. In many real-world scenarios, when faced with increased costs, businesses often transfer the burden to consumers through price hikes. This approach is straightforward, aligns with typical business practices, and reflects how retailers often respond to regulatory costs or taxes. It allows retailers to continue operations without directly absorbing the financial impact, thereby preserving their revenue.

Closing the Store: This option represents a more drastic response but is also a common outcome when the costs of doing business exceed profitability. If a retailer determines that the licensing fees significantly reduce their profit margins or push their operations into a loss, closing the store becomes a rational choice. This action is especially relevant in highly competitive markets or in areas with lower consumer spending power, where retailers may find it unfeasible to increase prices without losing customers.

These choices were selected for the model because they reflect the most likely and impactful actions retailers might take in response to new licensing fees, providing a clear and focused analysis of the potential economic and social effects of such policies. In the model, when licensing fees are introduced, retailers will randomly choose between these two actions, each with equal probability, simulating the varied responses that could occur in a real-world scenario

3.2.3 Town Types

To structure the simulation iterations effectively, the model first considers the classification of data zones based on availability and data zone classifications prevalent in the UK. Given the diverse urban and rural landscape in Scotland, it was essential to include both types—urban and rural—as distinct data zones for modelling. Urban areas generally represent higher average deprivation levels compared to rural areas, which might show below-average deprivation levels. However, within these broad categories, significant variations exist in socioeconomic conditions, leading to different levels of deprivation.

To address this, the model includes not only the general urban and rural classifications but also incorporates an additional category for highly deprived zones. This approach ensures a more nuanced representation of the diverse socioeconomic conditions across Scotland. Thus, the model features four key data zones:

- **Urban Areas**: Representing the general urban environment with average levels of deprivation.
- **Rural Areas**: Reflecting the typical conditions in rural settings with below-average deprivation.
- **Most Deprived Zones**: Highlighting areas with extreme levels of socioeconomic deprivation.
- **Least Deprived Zones**: Covering areas with minimal deprivation to provide a complete spectrum.

Each data zone or town type is evaluated under two policy schemes, with the urban-rural fee scheme additionally tested for specific zones. As a result: Urban and rural zones are assessed under all three policy schemes: universal, volumetric, and urban-rural fees and the Most deprived and least deprived zones are evaluated under the two applicable policy schemes: universal and volumetric.

This configuration results in a total of ten unique simulation iterations, providing a thorough analysis of the potential impacts of various policies across different socioeconomic and geographic contexts. The structure of these iterations is illustrated in the Figure, detailing the setup of the simulation framework.

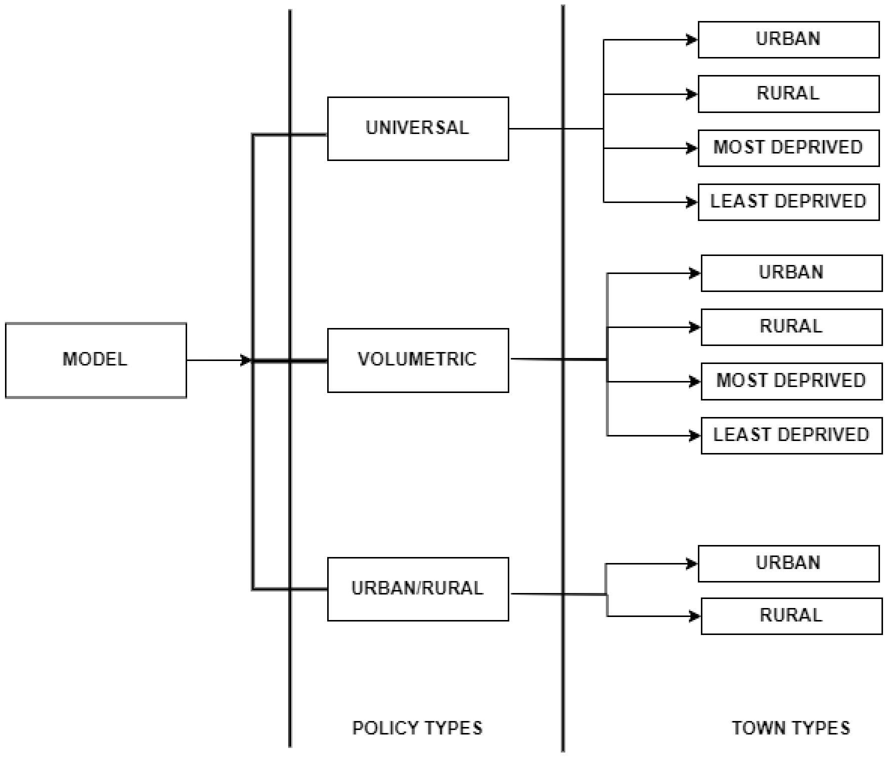

Figure 3.2: Simulation Conditions

3.3 Simulation Environment

In agent-based modelling, one of the most crucial aspects is creating a realistic simulation environment where agents can interact with one another, mimicking real-world dynamics. This environment serves as a virtual setup of the social settings or communities in which retailers and individuals—such as smokers, non-smokers, and those attempting to quit—live, interact, and influence each other's behaviours. It is within this structured framework that the agents' behaviours, such as smoking initiation and cessation, can be studied in relation to their peers and the broader societal context. In this section of the report, the design and structure of this simulation environment are explained, detailing how it has been configured to accurately represent the complexities of real-world social interactions and the factors that influence smoking behaviours.

3.3.1 Grid Structure

The model operates within a grid structure where two primary types of agents are situated: retailers and adult individuals (smokers and non-smokers). Retailers, both large and small, are distributed across the grid based on available empirical data and a random placement method. This ensures that their locations reflect real-world distributions. The grid dimensions in the model are carefully calculated to ensure a realistic representation of the population and their distribution across different areas. These dimensions are derived based on both the total population considered in the model and the density per square kilometre, reflecting the actual geographical distribution of people.

For the model, the data was from a sample of approximately 700 individuals across four different area types (urban, suburban, rural, and deprived areas). To scale this to the total population considered in the model, which is 20,000, the multiplication factor is applied. This factor is calculated by dividing the total population (20,000) by the average population size for each town type in the data sample. This scaling ensures that the model can effectively simulate a large enough population to capture the dynamics of smoking behaviour and cessation.

The grid size is then determined by multiplying this population scaling factor by the average Sq km density for each of the area types. This approach ensures that the grid accurately reflects the density and distribution of the population, allowing for realistic simulations of how individuals interact with each other and with their environment. By using this method, a grid was created that not only accommodates the total population of 20,000 but also accurately represents the varying densities across different areas.

3.3.2 Locations and its densities

In the model, the placement of businesses, homes, and retailers within the grid is carefully designed based on empirical data specific to various town or area types. This ensures that the simulation environment accurately reflects real-world density and distribution.

Business and Workplace Density: Business and workplace density is determined using the average number of such entities per square kilometre for each area type. Businesses, including workplaces, are distributed across the grid, with each grid cell representing a one-square-kilometre block. This proportional placement mirrors real-world concentrations, ensuring the simulation accurately reflects the distribution of businesses and workplaces in different areas. This setup is essential for simulating agents' daily routines, including their travel between home and work.

Residential Density: Homes are placed within the grid according to the average number of households per square kilometre for each area type. This data-driven approach ensures that each grid block's residential density accurately reflects the actual density observed in the corresponding town types. Realistic residential placement is crucial for modelling agent interactions, particularly regarding their proximity to workplaces and retailers. Retailers also adjust their pack prices annually based on the licence fees

Retailer Placement: Retailers, categorized as large or small, are placed in the grid based on the average number of each type per square kilometre for different town types. This classification, detailed in the retailer section of the report, includes specific characteristics such as retailer size and product offerings. By accurately distributing retailers in the grid, the model effectively simulates their accessibility and influence on smoking behaviour, particularly in how agents choose their cigarette purchase locations.

Data collection: In the model, the simulation runs for a total of six years. The first year serves as a base year, during which the sales simulation occurs without any fee structures in place. The fee structure is then implemented at the end of the first year, reflecting the typical timing of policy introductions. The subsequent five years are simulated under the policy conditions, allowing for the collection and analysis of data to assess the impact of the fee structures over this period. This approach ensures that the effects of the policy are evaluated over a substantial period, providing a clearer understanding of its long-term implications. Data collection is a critical aspect of the model, performed every year to avoid unnecessary complications from daily or monthly fluctuations. Key parameters collected include the number of smokers, average smoking rates, total cigarette consumption, average pack prices for both large and small retailers, and the impact of network effects on smoking cessation. The model simulates daily interactions (with one day equaling one simulation step), but the major updates and data resets occur annually, aligning with the broader policy and demographic changes modelled within this environment

This comprehensive placement strategy ensures that the simulation environment is both realistic and reflective of actual spatial dynamics, providing valuable insights into the interactions between agents, their behaviours, and their surrounding environment.

3.4 Agents

The agent-based model comprises two primary types of agents: retailers and individuals. The individuals category further includes smokers, quitters, and non-smokers. In the following section, the specific characteristics of these agents, the criteria used to define them, and the methodology for their integration into the model will be explored

3.4.1 Retailers

In the model, retailers are categorized into two types: large retailers and small retailers. Large retailers generally include supermarkets, while small retailers encompass various businesses such as convenience stores, petrol stations, clubs, and local shops. Both types of retailers are characterized by attributes including pack prices, annual and lifetime sales volumes, and gross profit margins.

For large retailers, pack prices and sales volumes are monitored annually. Gross profit is calculated by subtracting the cost price of cigarettes from the pack price, as specific operating costs are not provided, making net profit assessment infeasible. Small retailers employ a similar approach for determining gross profit and setting pack prices.

Retailers undertake three primary actions: selling cigarettes, paying annual licence fees according to the fee structure, and adjusting pack prices based on annual sales and fees. To manage the financial impact of licence fees, retailers adjust cigarette prices, ensuring that their sales revenue covers these costs. This pricing adjustment is made under the assumption that retailers can maintain their existing sales volumes and will pass the additional costs onto consumers, thereby safeguarding their profit margins

3.4.2 Population

In this model, the agents represent individuals who use tobacco, with the simulation based on a population of 20,000 people. This specific population size was chosen to provide a sufficiently large sample for analyzing the effects of different policy interventions while maintaining computational efficiency.

The age bracket of 34 to 45 years was selected for the simulation for several reasons. First, smoking prevalence tends to stabilize or slightly decrease within this age group, meaning that most individuals who smoke have already established the habit, and there is a lower likelihood of new smokers emerging. This stability in smoking behaviour makes it easier to study the impact of policy changes, such as the introduction of licence fee structures, on smoking cessation rates without the added complexity of accounting for smoking initiation.

Choosing a different age group, such as teenagers, would introduce additional challenges. Modelling younger age groups would require consideration of factors related to smoking initiation, such as peer pressure, parental influence, and social trends, which would significantly complicate the model. Given the time constraints and the desire to focus on the direct effects of policy on established smokers, the 34 to 45 age group was deemed most appropriate.

The model also accounts for age dynamics. Since the simulation focuses on the 35 to 45 age group, agents older than 45 are removed from the model at the end of each simulated year. Simultaneously, new agents entering the 35-year age bracket are added to maintain the population distribution. These new agents inherit characteristics similar to the initial population, including workplace and home locations, wages, smoking status, and cigarette consumption rates. Retailer preferences for these agents are determined by trip costs, with updates made annually to reflect changes in the population. According to existing Scottish census data, the population proportion for the 34 to 45 age group is 12.9%, while the proportion for the 24 to 35 age group, which may transition into the simulation's target age bracket, is 12.4%. These prevalence rates were used to establish the initial conditions for the simulation, ensuring that the model accurately reflects the demographic distribution of the population[26].

3.4.3 Agents

In this model, agents are categorized into three types: smokers, quitters, and non-smokers, each with specific attributes and behaviours. The integration of these agents into the model is based on a set of rules and interactions that mimic real-world behaviours. Retailers and individuals interact through the sale and purchase of tobacco products.

1. **Smokers:** Smokers are defined by characteristics such as their age, smoking frequency, preferred cigarette brands, and their sensitivity to price changes or anti-smoking campaigns. These attributes influence their smoking behaviour and decisions.

2. **Quitters:** Quitters are individuals who have successfully stopped smoking. Their behaviour is modelled to reflect their cessation status, which may be influenced by factors such as increased costs or policy changes.

3. **Non-smokers:** Non-smokers are individuals who have not engaged in smoking.

3.4.4 Parameters

As previously defined, the model focuses on agents within a specific age group. Each agent is assigned several parameters that help track their behaviour and interactions within the simulation. These parameters include a unique ID for tracking, their smoking status (whether they are smokers, quitters, or non-smokers), and their susceptibility to peer influence.

Additional parameters in the model include a list of neighbours (other agents they interact with), their home location, and their average wages. The model also tracks the number of days an agent goes without smoking, the number of cigarettes smoked daily and annually, the favourite retailer they visit to purchase cigarettes, and their overall purchase decisions. These parameters create a comprehensive profile for each agent, allowing the model to simulate and analyze smoking behaviours and decisions in a detailed and realistic manner In addition to the parameters mentioned, each agent in the model also has a designated workplace location, which is closely linked to their home location. This information is crucial for calculating the cost of purchasing cigarettes. From the smoker's perspective, the cost of purchase includes not only the price of the cigarettes but also the trip cost incurred when travelling to make the purchase.

In the model, the smoking rate for each agent is dynamically adjusted based on changes in the cost associated with purchasing cigarettes. The updated smoking rate is calculated using the price elasticity :

$$\text{smoking\_rate} = \text{smoking\_rate} \times (1 + \text{cost\_increment} \times \text{price\_elasticity\_coefficient}) \tag{3.1}$$

The cost increment represents the relative increase in the overall cost of purchasing cigarettes, which includes factors such as transportation, time, and other associated expenses. The smoking rate is updated each time there is a change in cost, whether due to a shift in the agent's preferred retailer or any other factors that affect the total cost of obtaining cigarettes. The price elasticity coefficient quantifies the sensitivity of smoking behaviour to changes in cost. The specific values for these coefficients are detailed in the Appendix A.3 Table a.7.

3.4.4.1 Trip Cost

The trip cost is determined by considering the agent's mode of transportation, their corresponding speed, average energy consumption, and the prevailing petrol price. By incorporating these factors, the model can accurately calculate the total cost of purchasing cigarettes for each agent, reflecting the real-world impact of travel on smoking behaviours and decisions. The model's structure incorporates workplace locations, home locations, and retailer locations, allowing for the calculation of the trip cost associated with purchasing cigarettes. Beyond the price of cigarettes, the trip cost represents the additional expense incurred by smokers when travelling to buy cigarettes.

Smokers, following a natural human tendency, prefer to buy from retailers that are either closer to their workplace or home, or conveniently located along their regular routes between these two points. To determine which retailers are most likely to be chosen by a smoker, the model calculates the cost of travelling to each retailer, known as the trip cost. Retailers that consistently offer the lowest trip cost for a smoker become the preferred choice for cigarette purchases. These retailers, where smokers decide to make their purchases regularly, are referred to as "favourite retailers" within the model.

To determine an agent's preferred retailer, the model incorporates transportation modes, such as public transport or private vehicles (e.g., cars), and considers the average speed and corresponding fuel costs for each mode. These factors are assigned based on existing data distributions. The selection of a "favourite retailer" involves a multi-step process. First, the model calculates the distance between an agent's home and workplace. Next, it computes the distances from the agent's home to each retailer and from each retailer to the workplace. The difference between these distances helps determine the trip cost associated with purchasing cigarettes from each retailer.

The trip cost for purchasing cigarettes is computed using the following formula:

$$\text{tc} = \left(\frac{d}{v} + \frac{1}{12}\right) \times w \times t + \left(d \times \frac{p}{e}\right) \tag{3.2}$$

where: d is the distance between the home and retailer, or the distance between the workplace and the retailer. v is the average speed of the transportation mode used. w is the hourly wage, set to £11.44. t represents the value assigned to the agent's time. p is the cost of fuel per unit. e is the fuel consumption rate of the vehicle.

The cost of cigarettes is determined by:

$$\text{cc} = \frac{dc}{20} \times rp \tag{3.3}$$

where: dc is the number of cigarettes the agent smokes daily,rp is the price per pack of cigarettes at the retailer.

The total cost of purchasing cigarettes, including the trip and cigarette costs, is calculated as:

$$\text{tc\_total} = \text{tc} + \text{cc} \tag{3.4}$$

If the total cost of purchasing cigarettes from a particular retailer—which includes both the cigarette cost and the trip cost—is the lowest among all available retailers for a specific agent, that retailer is designated as the agent's "favourite retailer." This assignment reflects the agent's preference for minimizing overall costs when purchasing cigarettes, aligning with realistic consumer behaviour where individuals tend to favour convenience and affordability.

In the model, the primary action of a smoker agent is to purchase cigarettes based on their daily consumption level, the amount of money they possess, and their current inventory of cigarettes. The agent assesses their cigarette needs and, if necessary, buys the required amount from their favourite retailer. The total cost of this purchase includes both the trip cost and the cigarette cost. This total is then deducted from the agent's available funds. If the agent's funds are insufficient to cover the total cost, they are unable to purchase cigarettes.

3.4.4.2 Cessation/Quitting Mechanism

Like in real-life scenarios, if an agent goes without purchasing cigarettes for an extended period, it is assumed that they have also gone without smoking. Specifically, if an agent goes more than 28 days without smoking, they are classified as a ”quitter.” This quitting can occur due to policy changes that increase the overall cost of purchasing cigarettes or other financial constraints, leading to what the model terms ”cost-induced quitting.”The number 28 was chosen based on the common understanding that it takes approximately 28 days to form or break a habit. This concept, while popularized in self-help literature, is rooted in Dr. Maxwell Maltz's observations [38], where he noted that it took around 21 days for individuals to adjust to physical changes. Over time, this idea was extended to 28 days to account for the complexity of behavioural shifts. This 28-day period has since become a widely accepted general guideline in habit formation and cessation studies,

Additionally, the model accounts for another form of quitting that happens through social influence within the network, where agents may quit smoking due to interactions with others who have already quit. This reflects the two primary pathways to quitting in real life: quitting due to external factors such as cost increases and quitting due to social influence. The model successfully captures both of these dynamics, allowing for a more comprehensive simulation of smoking behaviour and cessation.

3.5 Model Calibration and Validation

Model validation is a critical step in ensuring that a simulation accurately reflects real-world behaviours and outcomes. Without validation, a model's predictions could be unreliable or misleading, potentially leading to incorrect conclusions and ineffective policy recommendations. By validating the model, it is ensured that the simulation's results are grounded in reality, increasing the confidence in its predictions and making it a robust tool for analyzing the impact of different scenarios. Validation also helps identify any discrepancies between the model and real-world data, allowing for adjustments and improvements to be made, thereby enhancing the overall accuracy and reliability of the simulation.

Model validation was conducted using a base scenario, simulating the environment over five years. This base scenario did not include any licensing fee structures or additional conditions; it was a straightforward simulation where retailers sold tobacco products as usual, and smokers purchased them without any policy interventions.

The purpose of this validation was to ensure that the model accurately reflected real-world behaviour in the absence of policy changes. The average sales volume per store in each of the town types—urban, rural, most deprived, and least deprived—was tracked over the five years. These simulated sales volumes were then compared with historical data on Scottish retailer sales, broken down by town type.

This comparison allowed us to evaluate how closely the model's outputs aligned with actual sales patterns observed in Scotland. The goal was to validate that the model could reliably reproduce real-world sales data under normal conditions, thus establishing a solid foundation for subsequent simulations involving different policy scenarios

3.5.1 Weights

The first step of the model validation, focuses on incorporating data from various classifications, including urban, rural, most deprived, and least deprived areas. The available data was categorized into specific segments: urban most deprived, urban least deprived, rural most deprived, and rural least deprived. To align these segments with the broader classifications used in the model—urban, rural, most deprived, and least deprived—these segments had to be appropriately combined.

This combination was achieved using population data from the Scottish Household Survey, which provided insights into the distribution of people living under relative and severe poverty (defined as living below 60% and 50% of the UK median income, respectively). This population data was essential for accurately merging the categories into the broader classifications .[15][28]

The urban and rural classification in the model was based on the official Scottish Government definitions, which categorize areas with a population of less than 3,000 as rural. These rural areas are further divided into ”accessible rural” and ”remote rural.” Conversely, larger urban areas, other urban areas, accessible small towns, and remote small towns were classified as urban areas.[15][28]

By applying these classifications and poverty-level data, the weights necessary for combining the data into the categories used in the model are derived. These weights, as mentioned in the table below, along with validation results, ensured that the data inputs were accurately represented in the model, reflecting the true distribution and socioeconomic conditions across different geographic areas in Scotland.

The prevalence data incorporated into the model was derived from the Scottish Health Survey 2022 [33] and the Scottish Household Survey [31], utilizing SIMD [32](Scottish Index of Multiple Deprivation) quintiles for accurate representation of various area types. The smoking prevalence and quitting rates for each area type are as follows:

Area Type	Smoking Prevalence	Quitting Rate
Urban Areas	0.18	0.22
Rural Areas	0.15	0.21
Least-Deprived Areas	0.07	0.20
Most-Deprived Areas	0.25	0.24

Table 3.2: Smoking Prevalence and Quitting Rates by Area Type

3.5.2 Calibration:

Calibration is a crucial step in model development, aimed at ensuring that the model's outputs closely align with real-world data. This process involves adjusting parameters and inputs to enhance the model's accuracy and realism.

In this model, calibration focused on refining retailer density and other population parameters based on data sources detailed in Appendix A.1. Given that the model uses broader town types (urban, rural, least-deprived, and most-deprived) and the available data was segmented into more specific categories (urban least, urban most, rural least, and rural most), weights were applied to appropriately combine these data points. The weights for the population parameters are detailed in the Model Validation Results table in section 3.5.3.

3.5.2.1 Retailer Density

Retailer density values for urban and rural areas were derived from SIMD deciles, which were classified into more specific categories (urban least, urban most, rural least, and rural most). To align with the broader urban and rural classifications, a similar approach was used with the population parameters, applying corresponding weights to ensure consistency across the model.

Given the findings from the review of relevant literature, it was identified that place-based measures of deprivation often fail to accurately capture localized pockets of poverty, particularly in rural areas (Bailey et al., 2016). Based on the findings from the literature, it's evident that specific categories like "urban most" and "rural least" were not sufficient to accurately capture retailer densities in the most and least deprived areas.

To address this issue, the model was refined by adopting a more granular approach using SIMD deciles. Rather than relying on broad categories, the model incorporated a decile-based system, which divides areas into ten distinct levels of deprivation. Retailer densities were calculated based on these ten deciles, providing a more detailed representation of how tobacco retail distribution varies across different levels of socioeconomic status.

Specifically, the retailer densities for both the most and least deprived areas were derived from these deciles. By calculating smoking parameters corresponding to each decile, the model better represents the diverse population across different socioeconomic levels. This adjustment ensures that the model more accurately reflects the variations in retailer density and smoking behaviour within these decile-based groups

To address any potential inaccuracies in sales, the model was not solely assessed by relying on comparing the average sales data with model sales data. Instead, a comprehensive approach was taken to ensure that the data produced by the model fell within the 95% confidence interval of the overall sales.

3.5.2.2 Agent Parameters

Two key parameters played a critical role in calibrating the model to represent agent behaviour accurately. One of these was determining the initial amount of money that each agent possessed at the start of the simulation. This parameter is particularly challenging to model because it can vary widely between individuals, and there isn't a straightforward or standardized method to statistically or empirically determine the exact amount of money each person should have at the outset of the model.

To address this, the initial money parameter was calibrated alongside other aspects of the model. The goal was to ensure that the starting financial conditions for the agents did not lead to an unrealistic overestimation or underestimation of store sales. Through this calibration process, it was found that setting the initial amount of money to the equivalent of two months' salary produced the most accurate and realistic results.

This choice aligns with common financial behaviour, where individuals typically aim to maintain savings equivalent to six month's expenses in an emergency fund [1]. In this context, starting with two months of salary as the initial money was determined to be the optimal setting for this age group.

Another critical factor in calibrating the model was the average spending rate on tobacco for smokers. According to the ASH report [3], on average, 7.9% of annual income is spent on tobacco, though this rate varies across different deprivation levels. This expenditure rate was applied to the model, taking into account variations across urban and rural classifications as well as different deprivation levels.

3.5.3 Validation Results

	URBAN	RURAL	LEAST DEPRIVED (LP)	MOST DEPRIVED (MP)
Grid Size	38*38	206*206	109*109	43*43
Retailers	Small : 39 Large : 2	Small : 67 Large : 1	Small : 15 Large : 1	Small : 53 Large : 3
Prevalence	18%	15%	10%	22%
Total Sales Model	1,628,078.4	1,550,808.68	467,012.10	2,328,080.70
Avg Sales - Data	42206.26	26300.32	34440.54	49493.11
Avg Sales - Model	39709.24	22806.01	31134.14	42328.74
% difference	−6.2	−15.32	−10.62	−16.93
Z Score for 95% CI	−0.01	−0.15	−0.03	−0.13
IDEAL RANGE -	−1.96TO 1.96	−1.96 TO 1.96	−1.96 TO 1.96	−1.96 TO 1.96
Population	20,000	20,000	20,000	20,000
WEIGHTS	Urban : MP = 34, LP =66	Rural : MP = 26, LP =.74	LP : URBAN = 80, RURAL = 20	MP : URBAN = 86, RURAL = 14

Table 3.3: Model Validation Results-

Multiple iterations of the model are run for each scenario to account for the stochastic nature (i.e., the presence of randomness or unpredictability) of the system, ensuring that the inherent variability is comprehensively captured across all conditions in the simulation.

A significant factor affecting model calibration is the overall prevalence trend of smoking. Historically, smoking prevalence has been decreasing over time. However, the model uses current prevalence rates, which does not account for this natural decline when projecting into the future. As a result, the model might show slightly lower sales compared to actual historical sales, especially when simulating future scenarios where prevalence is expected to continue decreasing without any policy interventions.

The networks, which capture the influence of quitters and non-smokers on existing smokers, play a crucial role in the model. This network effect helps account for the observed decline in smoking rates, even in the absence of explicit policy changes. Therefore, while the model's future projections might show lower sales compared to historical data due to these factors, the network dynamic effectively captures these behavioural trends to a certain extent and contributes to the overall accuracy of the model.

The model's output aligns closely with historical data, as detailed in the table above, which presents a comprehensive comparison of key metrics. This table includes the grid size, the number of retailers, smoking prevalence rates by area type (urban, rural, least-deprived, most-deprived), average sales figures from the model versus historical data, total sales, total population, and the proportion of the population within the specified age group (34–45).

The model validation revealed that the actual sales data and the model's projections differ by 5% to 15% depending on the town type. This discrepancy can be attributed, in part, to the phenomenon of underreporting, where empirical evidence suggests that individuals tend to underreport their smoking habits by anywhere between 5% and 10%[24]. This under-reporting is particularly prevalent among younger smokers[14], who may feel a social stigma associated with admitting to higher cigarette consumption. So, when this underreporting is factored into the comparison, it is clear that the model output does not differ by more than 5% from the actual sales data.

The mean value of store sales in the model was further validated by calculating the z-scores for a 99% confidence interval of average sales, which ranged from -0.01 to -0.15. This range of z-scores indicates that the model's predictions align closely with historical data, confirming its accuracy and readiness for simulating various policies.

Chapter 4

Results and Analysis

In the first part of this section, the results are analyzed by comparing the outcomes of the policy models with the base model, which represents a scenario without any implemented policies. This comparison includes evaluating the impact of three policy structures for urban and rural areas and two policy structures for the most-deprived and least-deprived areas against the base case. The second part involves a comparative analysis of the regions, focusing on how the policies impact each area's socioeconomic conditions and further analysing the effect of peer influence.

4.1 Comparative Analysis

When comparing the urban town across the universal, volumetric, and urban-rural fee schemes, it is evident from the above figure analysis that all three schemes are effective in reducing smoking prevalence. However, the volumetric scheme is consistently less effective compared to the other two schemes. The urban-rural fee scheme emerges as the most effective, achieving the greatest reduction in smoking prevalence on average, even outperforming the universal scheme in urban settings. Conversely, the universal scheme results in a greater reduction in smoking prevalence in rural areas compared to the urban-rural scheme. This disparity can be primarily attributed to the fee structure in the urban-rural scheme, which imposes lower fees in rural areas and higher fees in urban areas compared to the universal scheme (as detailed in Section 3.2).

Additionally, the urban-rural scheme's targeted approach allows it to address the unique economic and social conditions of urban and rural areas more effectively, making it more adaptable to the specific needs of each region. This flexibility could explain its superior reduction in smoking prevalence in urban settings, where higher fees can be imposed without significantly harming economic activity, while in rural areas, lower fees prevent excessive financial strain on retailers and consumers. The universal scheme, with its consistent fee structure across all areas, lacks this adaptability, leading to its stronger reduction in smoking prevalence in rural areas but a weaker impact in urban environments.

Area	Universal (%)	Volumetric (%)	Urban/Rural (%)
Urban	23.93%	9.24%	26.31%
Rural	42.42%	24.79%	25.07%
Most Deprived	19.81%	10.67%	
Least Deprived	26.86%	6.29%	

Table 4.1: Relative Reduction in Number of Smokers Compared to Base Case for Policies over 5 Years. Refer to Appendix A.4 Figure A.3 for Number of smokers

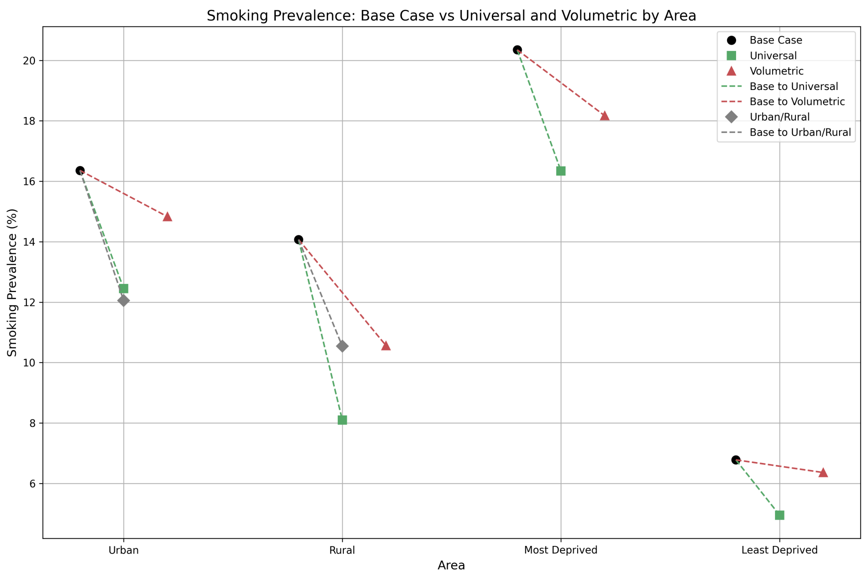

Figure 4.1: Smoking Prevalence Across Areas: Base Case vs Policies for Age Group 34-45

In the case of the most-deprived and least-deprived areas, a similar pattern is observed. All schemes contribute to reducing smoking rates, but the volumetric scheme consistently lags behind in effectiveness. For the least deprived areas, the trend persists, with the volumetric scheme being the least effective. However, it is notable that the reduction in smoking prevalence is less pronounced in the least deprived areas compared to other regions. This indicates that while the fees do lead to a decrease in prevalence, their effectiveness in these areas is not as prominent as in more deprived areas.

Across all four town types, the difference between the universal and volumetric fee schemes in terms of smoking prevalence among smokers tends to be around 1 to 2%, depending on the area. While this may seem like a small difference, it becomes significant when compared to Scotland's average smoking prevalence of around 15%. A 2% difference here translates to more than a 13% difference in smoking reduction between the two schemes, which underscores why the volumetric scheme is less effective than the universal scheme. A similar trend is observed when comparing the volumetric scheme with the Urban/Rural scheme, where the latter consistently outperforms the volumetric approach in reducing smoking prevalence.

4.1.1 Socioeconomic Impacts

4.1.1.1 Urban & Rural

When analyzing the five-year trend in the number of smokers in urban and rural areas from the image below, the volumetric scheme consistently shows the least impact on reducing the number of smokers. From a socioeconomic perspective, while this scheme does not exacerbate disparities between different income groups, its failure to significantly reduce the number of smokers undermines its overall effectiveness. This scheme's inability to make a substantial impact on smoking rates indicates that it does not fully meet the primary objective of reducing smoking.

In rural areas, the universal scheme significantly reduces the number of smokers by imposing higher uniform fees that effectively drive smokers to quit. However, while this approach is effective in lowering smoking rates, it also contributes to greater socioeconomic disparity. This can lead to increased financial strain on households, forcing them to allocate a larger portion of their income to tobacco products or struggle to quit without adequate support. Additionally, the uniform fees may lead to reduced access to essential goods and services as disposable income decreases, further widening the gap between more affluent and less affluent individuals. This imbalance can exacerbate existing socioeconomic inequalities potentially leading to negative outcomes such as increased poverty and decreased overall well-being in these communities.

In contrast, the urban-rural scheme's differentiated fee structure addresses these disparities more effectively. By imposing higher fees in urban areas where incomes are higher and lower fees in rural areas where incomes are generally lower, the urban-rural scheme minimizes the economic impact on disadvantaged populations and prevents widening socioeconomic gaps. Over the five-year period, the urban-rural scheme achieves results comparable to the universal scheme in urban areas, while also reducing smoking rates in rural areas similar to the volumetric scheme.

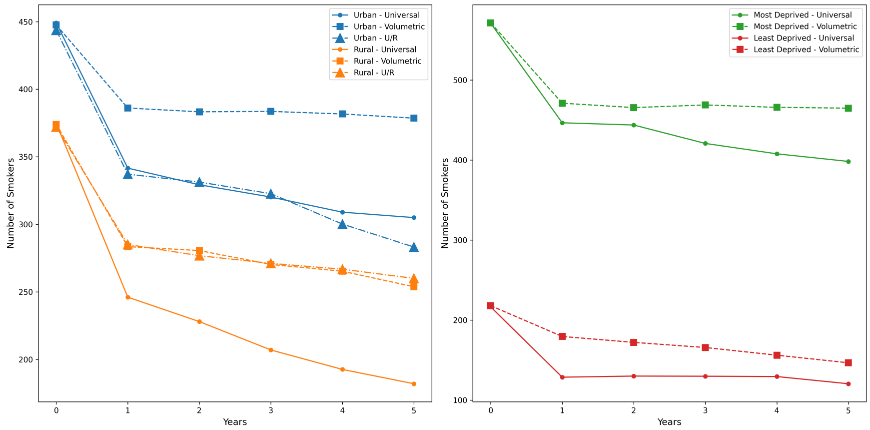

Figure 4.2: Number of smokers Trends by Area and Scheme Over 5 years. Refer to Appendix A.4 for the Normalized relative change chart of the same

4.1.1.2 Most Deprived and Least Deprived

When analyzing the five-year trend in the number of smokers under different schemes for the most deprived and least deprived, the volumetric scheme, while not as effective in reducing smoking prevalence, exhibits a more neutral impact from a socioeconomic standpoint. The modest and uniformly applied price increases under this scheme do not significantly alter the existing disparities between different regions, maintaining a relatively balanced effect on smokers across various socioeconomic groups. This approach avoids imposing excessive financial strain on any particular group, but its limited impact on reducing smoking rates raises concerns about its overall effectiveness in achieving public health goals.

In contrast, the universal scheme presents a starkly different outcome. The least deprived areas are the least affected by the stringent measures imposed by this scheme. Despite the higher fees and stricter policies that heavily impact other town types, these areas appear relatively insulated from these effects. The residents' financial stability allows them to absorb the additional costs without significantly altering their smoking behaviour, highlighting the resilience of wealthier populations to uniform policy measures.

On the other hand, the most deprived areas feel the universal scheme's impact. The significant financial burden placed on smokers in these regions could exacerbate existing socioeconomic disparities. The uniform fee structure fails to account for the economic vulnerabilities in these areas, leading to increased financial strain and potentially pushing more households into poverty. This widening gap between the most and least deprived regions underscores the limitations of a one-size-fits-all approach like the universal scheme. While effective in reducing smoking rates, this approach may inadvertently contribute to greater inequality, as those with fewer resources are disproportionately affected.

These findings suggest that a more nuanced, customized fee structure—such as the urban-rural scheme—would be more effective in balancing public health goals with socioeconomic equity. However, the results also indicate the need for further customization within the urban-rural scheme itself. In urban areas, particularly those with high levels of deprivation, additional adjustments may be necessary to ensure that the financial impact does not disproportionately affect the most vulnerable populations. Implementing differential fees within urban areas, tailored to varying levels of poverty, could help distribute the financial burden more equitably. This would encourage smoking cessation across all socioeconomic groups, ensuring that public health initiatives do not inadvertently deepen existing inequalities.

4.1.2 Impact of Peer Influence

Cessation of smoking occurs through two main mechanisms in the model: direct effects of policy constraints and indirect effects through social network influences, which are integrated into the model.

In urban areas, approximately 15% of quitters are influenced by their social networks, with the volumetric scheme exhibiting the highest impact at around 35% of the total quitters. However, this figure might be somewhat inflated, as the volumetric scheme is less effective overall in reducing smoking prevalence compared to other schemes. In rural areas, network influence contributes to about 20% of quitters. The volumetric and urban-rural schemes each show around 10%, while the universal scheme has a lower contribution. This lower percentage in the universal scheme is attributed to the fact that a higher number of people quit due to policy-driven constraints, making the relative contribution of peer influence appear smaller. Overall, the analysis indicates a significant network influence on smoking cessation, with contributions of at least 10%

in rural areas and 15% in urban areas.

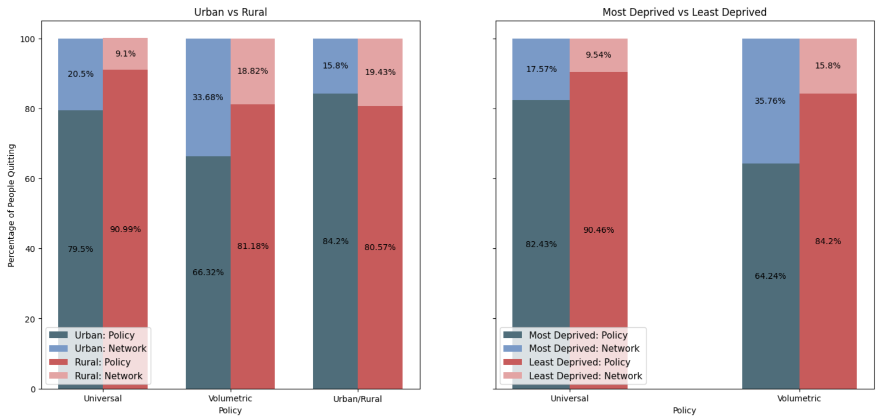

Figure 4.3: Quitter by Network Influence vs. Policy Influence by Area and Scheme Over 5 Years

A similar analysis of the most deprived and least deprived areas reveals consistent patterns regarding the impact of network influence on smoking cessation. For the most deprived areas, approximately 18% of quitters are influenced by their social networks, with peer influence accounting for around 35% of quitters under the volumetric scheme. In the least deprived areas, network influence accounts for approximately 10% of quitters under the universal scheme and 15-16% under the volumetric scheme. The lower impact of the universal scheme in these areas can be attributed to the scheme's high effectiveness in driving quitting through its own measures, which means that the contribution of peer influence, as a percentage of total quitters, appears relatively small. Overall, the findings indicate that network influence plays a notable role in smoking cessation, with at least 15% contribution in the most deprived areas and around 10% in the least deprived areas.

Despite variations in the effectiveness of different policy schemes, peer influence consistently contributes to at least 10% of the total number of quitters. In particular, the analysis reveals that even the least effective schemes still see a notable portion of smokers quitting due to peer influence, with impacts ranging from 10% to 20% in various contexts. This underscores the importance of integrating strategies that leverage peer support into smoking cessation policies. Therefore, alongside the primary policy schemes, it is essential to develop and implement complementary methods that harness the power of peer influence.

4.2 Findings and Policy Considerations & Implications

The findings and policy implications drawn from the results indicate that implementing a universal fee structure across different regions—urban, rural, most deprived, and least deprived—does not yield the desired outcomes. This underscores the need for differentiated fee structures, such as an urban-rural fee scheme, which could be more effective in addressing social income disparities without worsening them.

Furthermore, the results show that all fee structures tend to reduce smoking rates as intended. However, a constant fee structure leads to an initial sharp decline in smoking rates, followed by a plateau after a few years. On the other hand, an incremental fee structure could be considered, but it may place significant strain on retailers, requiring them to constantly raise prices. This could have unintended consequences, such as a rapid decrease in smoking that disrupts the local economy. A major concern with such a structure is its potential impact on retailers, particularly in rural areas where stores often serve as key access points for essential goods[32]. If not carefully managed, the intended reduction in smoking prevalence could inadvertently increase social and income disparities, by reducing access to essential services and widening existing gaps.

A more nuanced approach, such as a volumetric fee scheme, might be more favourable for retailers but may fall short of effectively curbing smoking habits, which is the primary objective of the policy. Policymakers need to proceed with caution, balancing the aim of reducing smoking prevalence with ensuring the socioeconomic sustainability of retailers. Differentiating fees between urban and rural areas appears to be a practical solution, but it is essential to avoid setting fees so high that they drive retailers out of business. The urban-rural fee structure, with further customization to account for intra-regional deprivations within both urban and rural areas, appears to be the most balanced and equitable approach to reducing smoking prevalence while minimizing the risk of exacerbating socioeconomic inequalities.

The network effect of peers is also a critical factor. The influence of quitters and non-smokers on remaining smokers indicates that, beyond financial constraints, social factors significantly impact smoking rates. This underscores the potential effectiveness of complementary strategies like social support groups and peer interventions that facilitate interactions among smokers & non-smokers. Utilizing funds from fee structures to support these initiatives allows the government to develop strategies that reduce smoking prevalence without straining budgets. This approach addresses both financial and social aspects of smoking reduction, fostering a supportive environment for quitting.

Chapter 5

Conclusion

5.1 Conclusion

The primary aim of this project was to explore and test the interaction of licence fees on the prevalence of smokers, specifically examining how these fees impact smoking communities with varying economic disparities in Scotland. To achieve this, different types of town types(urban, rural, most deprived and least deprived) were modelled using three distinct fee structures: volumetric, universal, and urban-rural schemes. Additionally, various behavioural aspects were incorporated into the agent-based modelling, including the influence of social networks among smokers. This modelling aimed to understand not only how financial constraints might drive individuals to quit smoking but also how social peer interactions influence quitting behaviour under different policy structures.

The study primarily focused on the 34-45 age group, where smoking habits tend to mature and stabilize over time based on historical data. To achieve this, the study modelled four distinct types of towns using agent-based modelling (ABM). The ABM approach was crucial in simulating complex interactions within populations, allowing for the exploration of three different fee structures: volumetric, universal, and urban-rural schemes. The models were designed to reflect not only the financial aspects of these policies but also incorporate various behavioural factors. Once the model was designed and agent parameters were finalized using existing population and business-related data from Scotland, it was calibrated and validated against the average sales of retail shops in specific regions, using historical average sales per store data available. The policy analysis was conducted, evaluating three policy structures for urban and rural areas and two policies for the most deprived and least-privileged regions. The analysis of the model results revealed several key findings regarding the effectiveness of different fee schemes in reducing smoking prevalence across various regions.

- In urban areas, the urban-rural fee scheme achieved the most significant reduction in smoking prevalence, while in rural areas, the universal fee scheme proved to be the most effective.
- When examining the most-deprived and least-deprived areas, the universal scheme was consistently the most successful in reducing smoking rates, although the volumetric scheme also contributed to a reduction in prevalence, albeit to a lesser extent. Interestingly, in the least deprived areas, the fee schemes had a more limited impact on smoking prevalence, as individuals in these areas were better able to absorb the financial effects of the fees.
- From these analyses, it became clear that the ideal fee structure would involve a differentiated approach, such as the urban-rural fee scheme, which offers different fees for urban and rural areas. This approach strikes a balance between reducing smoking prevalence and ensuring that rural areas do not experience disproportionate socioeconomic impacts, which could result from a universal fee structure.
- Volumetric schemes, while less effective in reducing prevalence, may be more favourable if the primary goal is to protect the interests of retailers, particularly smaller businesses.

The analysis suggests that an optimal government strategy would involve implementing an urban-rural fee structure customized to account for intraregional deprivations within these areas, complemented by additional strategies such as mass media campaigns and peer support initiatives to enhance quitting rates through peer influence. These complementary strategies could be funded by the revenue generated from the fees collected, thereby reducing the budgetary constraints on the government. Research in Scotland indicates that for every 1% reduction in smoking prevalence, approximately 3,700 households are lifted out of poverty[5]. Given that the various schemes discussed in this project are estimated to reduce smoking prevalence by 3-4% in urban-rural areas, 2-3% in the most deprived areas, and 1-1.5% in the least deprived areas, the potential impact is substantial. These reductions could lift over 10,000 households out of relative poverty in urban-rural areas, with 3,000 households benefiting in the least-deprived areas and approximately 7,400 households in the most deprived areas.

5.2 Limitations

Since the model relies on official sales data, which is legally reported, and smoking statistics, which are survey-based, the latter being influenced by under-reporting [24][14], this likely accounts for some of the observed variance between the model's validation output and actual sales figures. It is important to note that while this under-reporting may shift the model's output slightly—potentially within a 5% to 10% margin on the negative side—it does not fundamentally alter the model's conclusions or the observed smoking cessation trends. This limitation is acknowledged as a factor that may affect the model's precision but not its overall validity.

Additionally, every effort has been made to utilize the most recent data available from public records in Scotland, with the majority of the data coming from 2023 and some early 2024 sources. However, there are instances where only 2022 data was available, resulting in a slight one-year variation. While this gap is not expected to have a significant impact on the model's accuracy, it is acknowledged as a minor limitation. Efforts have been made to incorporate the latest data wherever possible, but in some cases, the use of older data was unavoidable.

5.3 Future Work

Future work could involve applying the model, initially based on hypothetical city characteristics, to real-world cities in Scotland, such as Glasgow or Edinburgh, to test policy pilots before full-scale implementation. Additionally, expanding the model to include various locations, such as health centres, and integrating health data could assess the overall impact of smoking policies on healthcare visits and service utilization. This broader perspective would help us understand the aftereffects of smoking policies and their implications from a more comprehensive viewpoint.

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Appendix A

Complementary Materials and Data

A.1 Data Sources

Retailer density, wage distribution, and cost price distribution for cigar retailers, as well as town type statistics, workplace data, business density, wage distribution, transport mode, and energy consumption (for trip costs), Sales Volume are based on publicly available data. These data sources include the ASH Scotland report and two additional research papers:

1. 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 [9].

2. 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[8].

Tobacco spending rate: ASH Scotland. The effect of smoking on personal finances and poverty in Scotland report.

These sources provide the necessary statistics and distributions to accurately model and analyze the relevant factors affecting smoking prevalence and socioeconomic disparities across different areas.

A.2 Policy Design Calculations

The policy design and fee structures are based on the findings of Roberto et al [36]. The key calculations for each policy from their research are outlined below. These findings have been instrumental in shaping the approach to tobacco license fee structures.

Universal Fee

The universal fee equation is given by:

$$Y = 158.5886x$$

where $x = 30$ (i.e., potential fee level = 30%).

Substituting x:

$$Y = 158.5886 \times 30 = 4,757.658 \text{ pounds/year}$$

- Universal fee: £4,757.66year

Urban/Rural Fee

The urban fee equation is given by:

$$Y = 182.4735x$$

Substituting $x = 30$:

$$Y = 182.4735 \times 30 = 5,474.205 \text{ pounds/year}$$

The rural fee equation is given by:

$$Y = 76.37849x$$

Substituting $x = 30$:

$$Y = 76.37849 \times 30 = 2,291.355 \text{ pounds/year}$$

Urban-Rural Scheme Fee:

- Urban fee: £5,474.21/year
- Rural fee: £2,291.36/year

Volumetric Fee

1. Pure Volume

The volumetric equation is given by:

$$Y = 0.3324x$$

where $x = 50$ (i.e., potential fee level = 50%).

The volumetric scheme fee is:

$$Y = 0.3324 \times 50 = 16.62 \text{ pounds/1,000 cigarette sticks sold}$$

2. Base Fee and Volume Fee

The base component and volumetric component can be calculated as follows:

- Value from urban fee equation:

$$Y = 182.4735x$$

where $x = 10$ (i.e., potential fee level = 10%):

$$Y = 182.4735 \times 10 = 1{,}824.735 \text{ pounds/year}$$

- Value from cigarette sub-fee equation:

$$Y = 0.3324x$$

where $x = 30$ (i.e., potential fee level = 30%):

$$Y = 0.3324 \times 30 = 9.972 \text{ pounds/1,000 cigarette sticks sold}$$

- Base component: £1,824/year
- Volumetric component: £9.97/1,000 cigarette sticks sold

A.3 Calculation of Weights for the Model

Town Type	Prevalence of Smokers	Prevalence of Quitters
Least Deprived (LP)	7.00%	20.00%
Most Deprived (MP)	25.00%	24.00%
Urban	18.00%	22.19%
Rural	15.35%	21.91%

Table A.1: Prevalence of Smokers and Quitters in Different Town Types

People in relative poverty AHC (below 60% of UK median income)	
All people	19%
Urban	20%
Rural	15%
People in severe poverty AHC (below 50% of UK median income)	
All people	14%
Urban	14%
Rural	11%

Table A.2: Poverty Rates by Region

Area Type	Total Population	Percentage
Large Urban Areas	2,061,049	37.62%
Other Urban Areas	1,843,792	33.64%
Accessible Small Towns	470,529	8.58%
Remote Small Towns	144,514	2.64%
Urban	4,519,884	
Accessible Rural	660,901	12.06%
Remote Rural	299,115	5.46%
Rural	960,016	
All Areas	5,479,900	100.00%

Table A.3: Population Distribution by Area Type in Scotland

Deprivation Type	Urban	Rural
MP (Most Deprived)	34%	26%
LP (Least Deprived)	66%	74%

Table A.4: Breakdown of Deprivation by Town Type (Urban and Rural Weights)

	Area Type	Percentage in Deprived Zone	Population	Weights
Most Deprived	Urban	34%	1,536,760.56	0.8603
	Rural	26%	249,604.16	0.1397
Least Deprived	Rural	74%	710,411.84	0.1923
	Urban	66%	2,983,123.44	0.8077

Table A.5: Weight Calculation for MP and LP Areas

Category	Urban	Rural	(MP)	(LP)
Prevalence of Smokers (%)	18	15	22	10
Prevalence of Quitters (%)	22	21	20	24

Table A.6: Prevalence of smokers and quitters across different areas.

SIMD Quintile	Price Elasticity Coefficient
SIMD1 (Most Deprived)	-1.35
SIMD2	-1.28
SIMD3	-1.21
SIMD4	-1.14
SIMD5 (Least Deprived)	-1.07

Table A.7: Price Elasticity Coefficients by SIMD Quintile

A.4 Results

The volumetric fee structure is calculated purely based on the volume of sticks with no base fees involved. The fee rate is $16.62 per 1000 sticks.

Category	Urban	Rural	MP	LP
Retailers	21	34	27	11
Smokers (Count)	438	351	541	185
Smokers (%) - After Policy	16.98%	13.60%	20.97%	7.17%
Quitters (Count)	28	21	28	61
Smokers (%) - Base Model	18%	15%	22%	10%
Avg Sales ($)	67,836.71	34,958.06	67,717.17	55,155

Table A.8: Data on retailers, smokers, quitters, and average sales across different areas for Pure Volumetric Policy

This plot shows the relative reduction in the number of smokers, normalized to 100% at Year 0. The left subplot covers Urban and Rural areas, and the right subplot covers the Most Deprived and Least Deprived areas, with lines representing different schemes (Universal, Volumetric, U/R) and colour-coded by town type

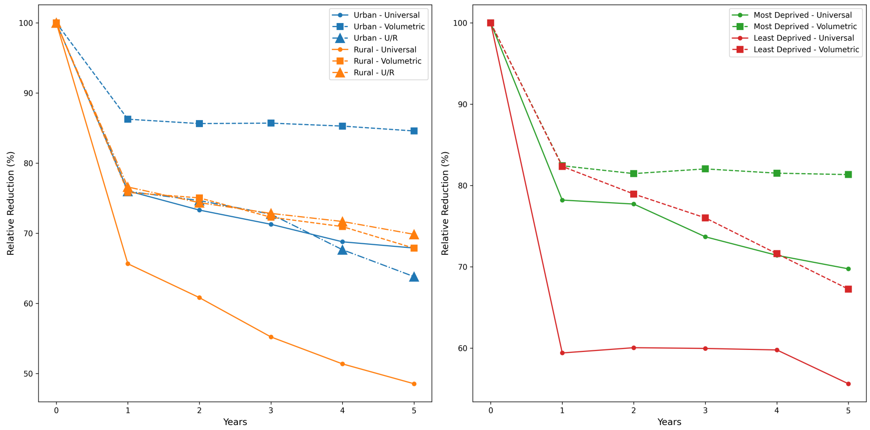

Figure A.1: Normalized Trends in Smokers (0-5 Years)

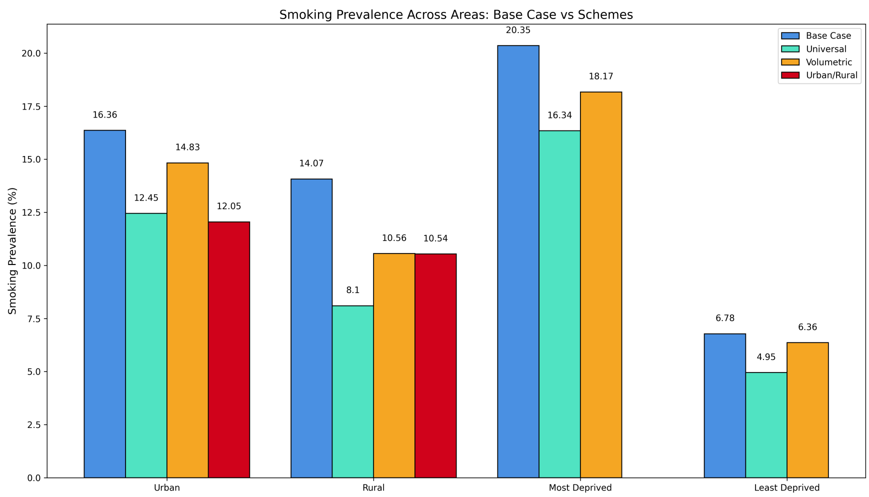

Figure A.2: Smoking Prevalence Across Areas: Base Case vs Policies for Age Group 34-45

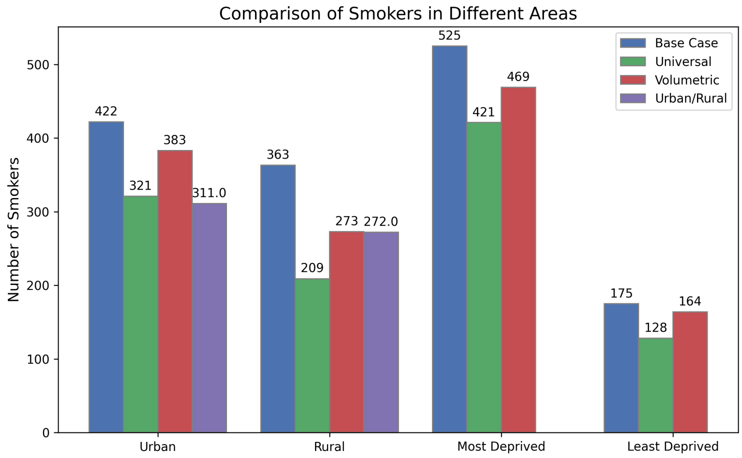

Figure A.3: Smoker Counts for Age Group 34-45 Across Town Types and Policy Scenarios, Based on a Population of 20,000