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Car-Free Households in Ireland: A Spatial Analysis Using Bayesian Negative Binomial Modelling

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Abstract

*A*chieving Ireland's net-zero greenhouse gas emissions target by 2050 requires a decisive shift away from private car dependency and towards more sustainable, inclusive modes of transport. Car-free households—those without regular access to a private vehicle—are central to this transition, yet little is known about the fine-grained drivers of car-free living across the country. Existing research tends to focus on broad national or regional trends, seldom accounting for the substantial spatial, socio-economic, and urban–rural variation that shapes car ownership patterns.

This dissertation addresses these gaps by investigating the determinants of car-free household prevalence at the Small Area (SA) level in Ireland. Drawing on 2022 Census Small Area Population Statistics (SAPS), the study integrates a suite of indicators, including the Pobal HP Deprivation Index, Public Transport Accessibility Levels (PTAL), and a novel multi-domain Attractions Index that measures access to local amenities and destinations. A Bayesian spatial modelling approach is applied, employing a negative binomial specification within an Integrated Nested Laplace Approximation (INLA) framework. The model incorporates spatial dependence via the Besag–York–Mollié 2 (BYM2) structure and is estimated separately for urban and rural areas to capture key differences in context, infrastructure, and policy needs.

Results show that the prevalence of car-free households is strongly shaped by public transport accessibility, material deprivation, household structure, and built environment features, but with pronounced differences between urban and rural settings. Notably, while public transport is the dominant driver in cities and towns, access to local amenities and socio-economic factors take precedence in rural areas. The study is the first in Ireland to incorporate a comprehensive area attractiveness index into spatial modelling of car-free households, providing unique evidence for planners and policymakers.

By combining high-resolution spatial data with advanced Bayesian methods, this research offers a robust, context-sensitive understanding of car-free living in Ireland. The findings inform targeted, equity-focused transport and spatial planning, supporting a just transition towards sustainable mobility and reduced car dependency.

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Chapter 1

Introduction

1.1 Context and Motivation

Global temperatures have risen at nearly twice the average rate since the 1980s, with 2024 recorded as the hottest year in history. Ireland faces continuing challenges in its efforts to achieve net-zero greenhouse gas (GHG) emissions, particularly in the transport sector. Although overall national emissions have recently begun to decline, transport emissions rose by 0.3% in 2023, making it one of the few sectors still showing growth. Private cars account for the majority of transport emissions, and in 2023, the sector contributed approximately 19.5% of total GHG emissions in Ireland (Department of Climate 2025).

The Climate Action Plan 2025 (CAP25) sets out an ambitious, legally binding ceiling of 6.1 $MtCO_2eq$ for the transport sector by 2030—a 50% reduction from 2018 levels. Policy levers under CAP25 include the 'Avoid–Shift–Improve' framework, which aims to reduce total vehicle kilometres travelled by 20%, halve fossil fuel use, and dramatically shift travel to public and active modes (Department of Climate 2025). Major initiatives such as BusConnects, Connecting Ireland, and the expansion of shared mobility are supported by parallel efforts in behavioural research and spatial planning reform.

Within this context, car-free households are of special significance. Car-free living is associated with lower per-capita emissions and higher use of sustainable modes, advancing both climate action and social equity objectives (Carroll, Benevenuto, and Caulfield 2021; Tikoudis et al. 2024). However, car-free status can also reflect transport disadvantage, particularly in rural and peri-urban areas where viable alternatives to car ownership are lacking (Rock and Ahern 2014). Thus, understanding the spatial and socio-economic distribution of car-free households is crucial for designing policies that are both effective and just.

Despite their policy relevance, car-free households remain under-researched in Ireland. Most existing studies analyse car ownership as a continuous or categorical variable, using survey or regional data that often obscure small-area variation and urban–rural differences (Caulfield 2011; Commins and Nolan 2010; Eakins 2015). International research highlights the complexity of these patterns, linking car-free living to income, age, household structure, built environment, accessibility, and cultural norms (De Gruyter et al. 2025; Van Eenoo 2023; Song and Wang 2017), but the Irish context, with its dispersed settlement requires specific investigation.

This dissertation addresses these gaps by investigating the drivers of car-free household prevalence at the Small Area level, using 2022 Census Small Area Population Statistics (SAPS), the Pobal HP Deprivation Index, Public Transport Accessibility Levels (PTAL), and a novel Attractions Index capturing multidimensional area amenities. A Bayesian spatial regression approach—specifically a negative binomial model estimated via Integrated Nested Laplace Approximation (INLA) with a Besag–York–Mollié 2 (BYM2) spatial structure—is used to provide the first spatially explicit, fine-scale model of car-free households in Ireland. Urban and rural areas are examined separately to capture differences in context, infrastructure, and need.

By delivering new evidence on the spatial, socio-economic, and infrastructural drivers of car-free living, this research aims to inform targeted, equity-oriented interventions for sustainable mobility. The project's methodological advances—especially the inclusion of detailed area attractiveness and robust spatial effects—contribute to both Irish and international literature on the geography of transport and climate policy.

1.2 Research Aim and Questions

The aim of this dissertation is to explore the spatial and socio-economic drivers of car-free households in Ireland using 2022 Small Area Population Statistics (SAPS) and additional datasets. It will examine how socio-demographic factors, public transport accessibility, and geographic context influence the rate of car-free households, and how these relationships may be different in urban and rural settings.

The study draws on multiple data sources; the 2022 Census, the Pobal HP Deprivation Index, Public Transport Accessibility Levels (PTAL), and a newly developed Attractions Index measuring access to destinations such as employment, education, and retail spaces. These datasets are integrated into a spatial modelling framework to account for geographic dependence and small-area variation. Five research questions will be addressed:

1. Which sociodemographic, housing and built form factors are associated with the prevalence of car-free households in Ireland at the Small Area level?

2. How does public transport availability and destination accessibility influence the likelihood of car-free households?

3. What is the relationship between socio-economic deprivation and the prevalence of car-free households at the Small Area level?

4. How do the factors influencing car-free household prevalence differ between urban and rural areas?

5. What are the policy-relevant implications of any identified associations for sustainable transport planning in Ireland?

The analysis aims to advance understanding of the spatial and socio-economic factors influencing car-free living, with findings intended to inform transport decarbonisation efforts and support the achievement of Ireland's sustainable mobility policy objectives

1.3 Contribution of the Study

This dissertation adds new evidence to academic research and policy discussions on sustainable transport. One contribution is its use of detailed, small-area data, which allows for a much closer look at patterns across Ireland. By analysing data from nearly 19,000 Small Areas, the study is able to identify local differences in transport needs and behaviours that would be hidden in studies using broader regions like counties or cities.

The study also provides methodological innovation by applying a Bayesian spatial negative binomial model estimated using Integrated Nested Laplace Approximation (INLA). This approach is well suited to modelling overdispersed count data while accounting for spatial autocorrelation and small-area instability. The inclusion of structured and unstructured spatial random effects via the Besag-York-Mollié 2 (BYM2) framework allows for improved model fit and more robust estimates, particularly in areas with sparse data. Unlike traditional regression techniques, the Bayesian framework used here allows for quantification of uncertainty and spatial effects, making the results more interpretable and actionable for policymakers who need to balance evidence with risk and geographic variation.

This study makes a theoretical contribution by offering a new way to think about car-free living. Rather than seeing it only as a sign of disadvantage or lack of choice, the research recognises that some households may live without a car because of personal preferences, access to good public transport, or supportive urban design. By assuming that car-free living can reflect both constraint and choice, the study helps build a more balanced understanding of transport disadvantage and sustainable travel behaviour. It highlights how car-free households relate to wider issues like equity, land use planning, and access to opportunities.

Finally, the research has strong policy relevance. Findings from this study can inform the development of geographically targeted interventions that align with the CAP25 goals of reducing car dependency, improving transport equity, and increasing the share of sustainable transport modes. In particular, the results may help identify areas where households are car-free by necessity rather than by choice, and locations where enhanced public or shared mobility services, or improved active travel infrastructure could have the greatest impact. The urban/rural differentiation also supports a tailored approach to policy development, in line with current planning of Ireland's transport systems.

1.4 Structure of the Dissertation

Following this introduction, the remainder of this dissertation is organised as follows.

Chapter 2 provides a comprehensive literature review, beginning with conceptual definitions of car-free households and a synthesis of empirical studies on their socio-demographic, socio-economic, built environment, public transport and area attractiveness determinants. This chapter also discusses urban–rural patterns, international policy lessons, methodological approaches, and concludes by identifying key research gaps that motivate the present study.

Chapter 3 outlines the data sources, processing steps, and variable construction procedures. It details the integration of 2022 Census Small Area Population Statistics, the Pobal HP Deprivation Index, Public Transport Accessibility Levels, and a suite of local area attractions indices. This chapter also describes the creation and cleaning of variables, the management of missing data, and the preliminary exploratory analyses used to assess model assumptions.

Chapter 4 describes the overall methodological framework. It introduces the negative binomial regression model with Bayesian inference via INLA, explains the rationale for spatial modelling using the BYM2 specification, and details the modelling of urban–rural heterogeneity, prior selection, and model evaluation procedures. The approach to interpreting model effects is also discussed.

Chapter 5 presents the main results of the spatial analysis. The findings are structured thematically, first contrasting urban and rural effects, then providing detailed breakdowns for socio-demographic, socio-economic, built environment, and transport accessibility variables in both contexts. Spatial and dispersion parameter estimates, as well as model diagnostics, are reported.

Chapter 6 discusses the results in the context of the existing literature and Irish transport policy. It provides a summary of the principal findings, interprets them in relation to previous research, reflects on methodological strengths and limitations, and outlines directions for future research.

Finally, Chapter 7 concludes the dissertation by synthesising the main contributions and highlighting the practical implications for car-free research and policy development in Ireland.

Chapter 2

Literature Review

Understanding the determinants and spatial distribution of car-free (or zero-car) households is essential to support transport and socio-economic policy. As policies increasingly seek to encourage more sustainable mobility and reduce car dependency, research into the determinants of car-free living is both timely and relevant (Carroll, Benevenuto, and Caulfield 2021; Currans et al. 2023; Eakins 2015). While there is substantial literature on car ownership, travel behaviour, and transport disadvantage, much less attention has been devoted to the specific conditions and spatial patterns associated with households that do not own a private car—particularly at fine geographic scales in the Irish context (Commins and Nolan 2010; Eakins 2015).

This chapter provides a review of theoretical and empirical contributions from Irish and international studies on car-free households. The review begins by summarising how car-free status is conceptualised and measured, highlighting definitional variation. It then synthesises evidence on the influence of socio-demographic, socio-economic, built environment, public transport, and area attractiveness factors, with attention to urban–rural differences and spatial clustering. Methodological approaches and advances in spatial and Bayesian modelling are also considered, alongside policy-relevant findings. Throughout, the chapter identifies key gaps in the literature, particularly the lack of spatially explicit, fine-grained analysis and the omission of comprehensive measures of area attractiveness, that directly inform the design and focus of this dissertation.

2.1 Conceptualising Car-Free Households

In the academic literature, a car-free household is generally understood as one in which no member owns or has regular access to a private car. Despite this straightforward description, studies highlight that the concept can be interpreted in different ways. Some authors emphasise that definitions may vary depending on whether shared, company, or communal vehicles are included, and note that official statistics may not always fully capture all forms of car access within households (Commins and Nolan 2010; Eakins 2015).

Theoretical frameworks distinguish between households that are "car-free by choice", opting not to own a car due to lifestyle preference or urban living, and those that are "car-free by constraint" or necessity, for example due to affordability, age, or other barriers. This distinction is reflected in the literature by references to "transport disadvantage" or "captivity," where car-free status is a result of limited options rather than personal preference (Commins and Nolan 2010; Carroll, Benevenuto, and Caulfield 2021; Eakins 2013). Recent research has also drawn attention to the emergence of voluntarily car-free households, particularly in contexts with greater mobility alternatives (Carroll, Caulfield, and Ahern 2017; Tikoudis et al. 2024). However, most available data do not allow researchers to reliably distinguish between voluntary and involuntary non-ownership.

How car-free households are conceptualised in research can have a substantial impact on the interpretation of findings and the design of policy. It is therefore important to state clearly how car-free status is defined. In this study, a car-free household is defined as one in which no member reports ownership of a private car, consistent with the definition used in national census data. This approach focuses on the absence of privately owned vehicles, while recognising that some forms of access—such as company cars or shared vehicles—may not be fully captured.

2.2 Determinants of Car-Free Households

2.2.1 Socio-Demographic Determinants

Socio-demographic characteristics play a crucial role in shaping patterns of car ownership and car-free households. Age is one of the most consistent factors: both younger adults and older individuals are more likely to live without a car, particularly in urban settings and apartment housing (De Gruyter et al. 2025; Van Eenoo 2023; Commins and Nolan 2010). Cohort effects are also evident, with recent research showing that younger adults, especially in high-density environments, are increasingly delaying or avoiding car acquisition due to factors such as lower incomes, postponed life milestones, and changing attitudes towards car ownership (Liu et al. 2020; Zhong and Lee 2017; Van Eenoo 2023). However, while some affluent urban residents are choosing car-free lifestyles, many zero-car households continue to face constraints related to affordability or lack of alternatives (Van Eenoo 2023; De Gruyter et al. 2025; Toy, Whitmarsh, and Sun 2025).

Household structure further shapes car ownership outcomes. Single-person, non-family, and single-parent households are observed to have higher rates of car-free status than larger family or multi-adult households (De Gruyter et al. 2025; Van Eenoo 2023; Commins and Nolan 2010; Caulfield 2011). Life events such as marriage, partnership formation, or having children are major triggers for acquiring a car, while giving up car ownership is relatively uncommon once a household is motorised (Clark, Chatterjee, and Melia 2016; Toy, Whitmarsh, and Sun 2025).

Evidence on gender is less consistent, though some studies indicate that gender differences may appear in particular life stages or contexts (Van Eenoo 2023). Migration background has also been identified as a relevant dimension: households with recent migration histories or non-citizen status are sometimes found to be more likely to be car-free, especially in large urban areas or among renters (Van Eenoo 2023).

Taken together, the literature demonstrates that age, cohort, household structure, gender, and migration background are all key socio-demographic determinants underlying variation in car ownership and the prevalence of car-free households.

2.2.2 Socio-Economic Determinants

Socio-economic status emerges as an important influence on car ownership patterns across the literature. Multiple studies in both Irish and international contexts report that households with lower incomes or living in more deprived areas are significantly more likely to be car-free (Commins and Nolan 2010; De Gruyter et al. 2025; Van Eenoo 2023; Caulfield 2011; McGoldrick and Caulfield 2015; Tol and HENNESSY 2011; Eakins 2015; Eakins 2013). In Ireland, research has shown that car ownership levels closely follow economic cycles, rising during times of prosperity and declining in economic downturns, with households on lower incomes most affected by these shifts (Eakins 2015; Tol and HENNESSY 2011).

Studies also show that income, employment status, and housing tenure are strongly associated with the likelihood of car ownership. Commins and Nolan (2010) and Caulfield (2011) both find that individuals with higher income, stable employment, and home ownership are much more likely to own at least one car. Conversely, households with lower income, unemployment, or precarious work are more frequently car-free (Commins and Nolan 2010; Caulfield 2011; McGoldrick and Caulfield 2015). International research echoes these findings, noting that zero-car households are commonly found among lower-income, single, and rental households in urban settings (De Gruyter et al. 2025; Van Eenoo 2023; Toy, Whitmarsh, and Sun 2025).

Economic constraints are a core component of what the literature describes as "transport poverty" or "transport disadvantage." Car-free households experiencing socio-economic disadvantage often face limited mobility, with restricted access to employment, services, and social opportunities (Carroll, Benevenuto, and Caulfield 2021; Toy, Whitmarsh, and Sun 2025; Van Eenoo 2023). This has been particularly highlighted in Irish rural contexts, where limited transport alternatives compound social exclusion for those unable to afford a car (Carroll, Benevenuto, and Caulfield 2021). Several studies stress the importance of distinguishing between households that are car-free by choice and those that are car-free by necessity or constraint (Toy, Whitmarsh, and Sun 2025; De Gruyter et al. 2025; Commins and Nolan 2010).

While not all car-free households are socio-economically deprived, the intersection of deprivation, income, employment, and car access remains central to understanding patterns of car-free living and their policy implications.

2.2.3 Built Environment Determinants

The built environment consistently emerges as a significant determinant of car ownership and the prevalence of car-free households. Dwelling type and housing density are central: studies report that residents of apartments, multi-family housing, and high-density urban neighbourhoods are considerably more likely to live without a car compared to those in detached houses or lower-density areas (De Gruyter et al. 2025; Van Eenoo 2023; Caulfield 2011; McGoldrick and Caulfield 2015; Song and Wang 2017; Clark, Chatterjee, and Melia 2016; Currans et al. 2023). Smaller dwelling size, limited off-street parking, and high-rise living further reduce the likelihood of car ownership (De Gruyter et al. 2025; Song and Wang 2017; Currans et al. 2023).

Tenure status is another important factor, with research indicating that renters tend to have lower rates of car ownership than homeowners, even after accounting for other characteristics (De Gruyter et al. 2025; Van Eenoo 2023; McGoldrick and Caulfield 2015). Housing quality, including building age, maintenance standards, and access to private parking, also shapes car ownership patterns, while high-quality shared spaces and amenities may support car-free living, particularly in urban settings (Song and Wang 2017; Weng et al. 2024).

The proximity of housing to jobs, shops, schools, and public transport is highlighted across both Irish and international studies as a key enabler of car-free households. Research demonstrates that areas with greater destination accessibility and more walkable environments tend to have lower car ownership rates, supporting alternative modes such as walking, cycling, and transit (Song and Wang 2017; Laviolette et al. 2022; Weng et al. 2024). Urban design elements such as street connectivity and the quality of the public realm can further encourage car-free lifestyles.

In the Irish context, shifts in urban form—such as increased apartment construction, urban densification, and changing patterns of suburban development—are linked to evolving car ownership trends (Caulfield 2011; McGoldrick and Caulfield 2015; Commins and Nolan 2010; Nolan 2010). However, the continued provision of car parking and car-oriented layouts in new developments can undermine efforts to promote car-free living.

Taken together, the literature demonstrates that dwelling type, tenure, density, housing quality, parking provision, destination accessibility, and urban design all interact to shape the likelihood and feasibility of car-free living, with effects varying by spatial context and across countries.

2.2.4 Public Transport and Area Attractiveness

Access to public transport and proximity to key destinations are widely recognised as central influences on car ownership and the prevalence of car-free households. International research consistently demonstrates that improvements in public transport provision and service quality can reduce household car ownership over time. For example, Mulalic and Rouwendal (2020) use a residential sorting model for the Copenhagen metropolitan area to show that enhanced public transport leads to lower car ownership, especially in compact urban settings (Mulalic and Rouwendal 2020). Laviolette et al. (2022) find, through spatial modelling in Canadian cities, that car-free living is more common where access to transit is high and built environment features are supportive (Laviolette et al. 2022).

Methodological advances have expanded how public transport accessibility is evaluated. Yadav, Mepparambath, and Patil (2024) introduce a framework that integrates Public Transport Accessibility Levels (PTAL) with analyses of service gaps, helping to identify areas that are underserved by transit and likely to be more reliant on private vehicles (Yadav, Mepparambath, and Patil 2024). Song and Wang (2017) highlight that lower automobile ownership is observed where density is higher, amenities are closer, and public transport is more accessible, emphasising the spatial relationship between land use and transport options (Song and Wang 2017). Weng et al. (2024) also explore the spatial and temporal links between built environment features and public transport competitiveness, further illustrating the dynamic relationship between area attributes and transport mode choices (Weng et al. 2024).

While several studies have examined the relationship between car ownership and factors such as proximity to amenities, land use mix, and public transport accessibility (Song and Wang 2017; Weng et al. 2024; Yadav, Mepparambath, and Patil 2024), none of the reviewed literature explicitly measures or models "area attractiveness" as an independent variable in relation to car ownership. The inclusion of detailed area attractiveness data—encompassing a range of destination types and amenities—represents a notable strength and contribution of the present dissertation, addressing a gap in previous research.

Collectively, the literature underlines that the quality and availability of public transport, as well as the accessibility and proximity of key destinations, are critical for supporting car-free lifestyles. These relationships manifest differently across urban and rural contexts, with significant implications for transport planning and policy. However, while previous studies have considered factors such as land use mix and access to amenities, none explicitly model "area attractiveness" as an independent influence on car ownership. The present dissertation addresses this gap by incorporating a detailed area attractiveness index—encompassing a broad range of destination types and amenities—thereby providing a novel perspective on the drivers of car-free living.

2.3 Urban–Rural Patterns

A recurring theme in the literature is the clear distinction between urban and rural patterns of car ownership and car-free living. Spatial clustering of zero-car or car-free households is most frequently observed in high-density urban centres, where better public transport access and proximity to amenities make car-free lifestyles more feasible (Carroll, Benevenuto, and Caulfield 2021; De Gruyter et al. 2025; Van Eenoo 2023; Song and Wang 2017). In contrast, rural and suburban areas, characterised by lower residential densities and greater distances to key destinations, display much lower rates of car-free households.

The Irish context reflects these broader patterns, with pronounced urban–rural differences. Carroll, Benevenuto, and Caulfield (2021) demonstrate that limited public transport and long distances to essential services in rural Ireland create significant barriers to car-free living (Carroll, Benevenuto, and Caulfield 2021). While policy initiatives such as organised car sharing, rural car pooling schemes, and shared mobility hubs have been proposed to reduce car dependency in less urbanised regions, uptake remains concentrated in cities and towns, with limited expansion into rural areas (Rabbitt and Ghosh 2013; Rabbitt and Ghosh 2016; McGreevy 2019; *Shared Mobility Hubs: Issues, Challenges and Opportunites* 2024).

Spatial modelling techniques have been employed to further understand these patterns. Song and Wang (2017) find strong associations between automobile ownership, urban form, and land use in South Florida (Song and Wang 2017). Laviolette et al. (2022) show that built environment characteristics and transit access interact with urban–rural context to shape car ownership outcomes in Canadian cities (Laviolette et al. 2022), while Mulalic and Rouwendal (2020) highlight how improved public transport in compact urban settings can encourage spatial clustering of car-free households in the Copenhagen metropolitan area (Mulalic and Rouwendal 2020).

Overall, the literature demonstrates strong spatial clustering and marked urban–rural heterogeneity in car-free household prevalence. These patterns underscore the importance of spatially explicit modelling approaches for understanding the determinants of car-free living across diverse settlement types.

2.4 Policy Implications and International Lessons

The literature offers several insights for policymakers seeking to promote sustainable transport and reduce car dependency. International evidence suggests that comprehensive policies supporting public transport, compact urban design, and alternative mobility options can lead to sustained reductions in car ownership. For example, Mulalic and Rouwendal (2020) show that improvements in public transport access, in combination with residential sorting and urban planning strategies, have a lasting impact on household car ownership decisions in the Copenhagen metropolitan area (Mulalic and Rouwendal 2020). Similarly, Laviolette et al. (2022) highlight the importance of integrating spatial planning and transit service provision in Canadian cities to encourage car-free living (Laviolette et al. 2022).

The transition to more sustainable transport behaviours is not only a matter of infrastructure or income—it also involves cultural and behavioural change. Wieczorek, Raven and Berkhout (2015) emphasise the importance of sustainability experiments and transnational learning in driving behavioural transitions, using the example of solar energy diffusion in India. While not specific to transport, their findings suggest that policies to promote car-free living may need to foster broader societal change and support innovation (Wieczorek, Raven, and Berkhout 2015).

In Ireland, policy-oriented studies emphasise that the urban–rural divide presents unique challenges for reducing car dependency (Carroll, Benevenuto, and Caulfield 2021; Rabbitt and Ghosh 2013). Rabbitt and Ghosh (2013, 2016) evaluate car sharing schemes in Ireland and find economic and environmental benefits, though uptake is still limited outside city centres (Rabbitt and Ghosh 2013; Rabbitt and Ghosh 2016). Initiatives such as shared mobility hubs and rural car pooling schemes (*Shared Mobility Hubs: Issues, Challenges and Opportunites* 2024; McGreevy 2019) are identified as promising but currently limited in scale and impact.

Recent shocks such as the COVID-19 pandemic have also affected travel behaviour and transport demand. Al-Akioui and Monzón (2023) used spatial analysis to examine how mobility patterns in Madrid were altered during the pandemic, with lasting impacts on travel preferences and demand. These findings may have implications for post-pandemic transport planning in Ireland, especially in terms of remote work and support for active modes of travel (Al-Akioui and Monzón 2023).

The literature also identifies the need for policies to address equity concerns. Studies note that car-free households are often concentrated among lower-income, single-person, or rental households, raising questions about transport poverty and social exclusion (De Gruyter et al. 2025; Van Eenoo 2023). Policy responses must therefore balance goals for sustainability with the need to ensure mobility for all population groups.

Overall, international and Irish experience demonstrates that achieving reductions in car ownership requires a coordinated approach to land use, public transport investment, innovation, and shared mobility, as well as a focus on social equity and cultural change.

2.5 Methodological Approaches in the Literature

The literature on car ownership employs a broad array of statistical and spatial modelling approaches, often determined by available data and research objectives. Poisson and negative binomial regression models are widely used to analyse the count of vehicles per household, reflecting the discrete and frequently skewed nature of car ownership data (Gardner, Mulvey, and Shaw 1995; Eakins 2015; Eakins 2013). To address excess zeros and overdispersion, several studies adopt zero-inflated and overdispersed count models (Lambert 1992; Ridout, Demetrio, and Hinde 1998).

Beyond count models, multinomial, ordered, and discrete choice models are applied to distinguish among categories of ownership such as zero-car, one-car, or multi-car households (Commins and Nolan 2010; De Gruyter et al. 2025; Papu Carrone, Monteiro, and Rich 2021; Krisztin, Piribauer, and Wogerer 2022). Binary (yes/no) car ownership outcomes are also frequently modelled using logistic regression or Bayesian binary frameworks, particularly in studies focused on zero-car prevalence (Carroll, Benevenuto, and Caulfield 2021; De Gruyter et al. 2025; Van Eenoo 2023; Watanabe and Maruyama 2024).

Spatial and geographically weighted models are increasingly used to capture the spatial clustering and heterogeneity of car ownership. For example, Song and Wang (2017) model spatial relationships between automobile ownership, land use, and neighbourhood characteristics, while Laviolette et al. (2022) and Krisztin et al. (2022) apply spatial regression and multinomial logit models to assess built environment and policy influences (Song and Wang 2017; Laviolette et al. 2022; Krisztin, Piribauer, and Wogerer 2022). Geographically weighted regression has been applied to transport outcomes to allow for local variation in the strength of predictors (Günther Klar 2021).

Recent advances include the use of Bayesian hierarchical and spatial models, which offer flexibility for handling complex data structures, spatial random effects, and uncertainty in parameter estimates (Smith et al. 2024; Morales-Otero and Núñez-Antón 2021; Watanabe and Maruyama 2024). The choice of model is influenced by the nature of the research question, the structure of the data, and the presence of spatial dependence.

Across these studies, the most common data sources are census and large-scale household surveys (Eakins 2015; Commins and Nolan 2010; McGoldrick and Caulfield 2015; De Gruyter et al. 2025), complemented in some cases by spatial, administrative, or environmental datasets (Song and Wang 2017; Laviolette et al. 2022; Krisztin, Piribauer, and Wogerer 2022). Each modelling approach brings distinct strengths and limitations, highlighting the importance of methodological transparency and model fit assessment in car ownership research.

2.6 Synthesis of Evidence and Research Gaps

The literature consistently shows that car-free households are shaped by a combination of socio-demographic, socio-economic, and built environment factors, with strong evidence for spatial clustering and pronounced urban–rural heterogeneity (Carroll, Benevenuto, and Caulfield 2021; De Gruyter et al. 2025; Van Eenoo 2023; Song and Wang 2017). Irish and international studies highlight the importance of income, deprivation, household structure, tenure, built environment, and access to public transport in explaining variations in car ownership (Commins and Nolan 2010; Caulfield 2011; Laviolette et al. 2022; McGoldrick and Caulfield 2015). Areas with higher density, better amenities, and improved public transport are more likely to support car-free living, while rural and low-density areas remain heavily car-dependent.

Despite these advances, three notable gaps remain in the existing literature:

1. **Integrated spatial modelling for Ireland:** There is limited research that applies spatially explicit statistical models to the drivers of car-free households at a fine geographic scale in the Irish context, particularly models that jointly account for urban–rural variation, built environment, and accessibility.

2. **Comprehensive accessibility and "area attractiveness":** Existing studies seldom incorporate a detailed, multi-dimensional measure of area attractiveness—including proximity to a broad range of destinations and amenities—into spatial models of car ownership.

3. **Fine-grained, multi-factor analysis:** There remains a need for analyses that simultaneously examine socio-demographic, socio-economic, built environment, and accessibility factors at the small-area level, in a single unified modelling framework.

This dissertation addresses these gaps by:

- Applying a spatially structured Bayesian negative binomial model to recent Irish Census data, with explicit modelling of spatial effects and urban–rural differences;

- Incorporating a novel, detailed measure of area attractiveness—covering multiple types of destinations and amenities—absent from prior car ownership studies;

- Jointly modelling the roles of socio-demographic, socio-economic, built environment, public transpor, and area attractiveness variables to provide a holistic view of the drivers of car-free households at small-area scale in Ireland;

- Producing new evidence on spatial patterns and context-specific drivers to inform sustainable transport and spatial planning.

By filling these specific gaps, the study aims to advance both academic understanding and policy practice on the determinants and spatial dynamics of car-free living in Ireland.

2.7 Summary

The reviewed literature offers insights into the determinants and spatial patterns of car-free households. Evidence from Ireland and internationally demonstrates that car ownership is shaped by a complex interactions between individual, structural, and spatial factors. Key determinants include income, deprivation, housing characteristics, transport accessibility, and urban form. Methodologically, spatial regression and Bayesian models provide valuable methods for analysing spatial patterns of car-free living.

Chapter 3

Data Sources, Processing, and Variable Construction

This chapter outlines the workflow for preparing the data used in this study. Section 3.1 describes the data sources, including Census Small Area Population Statistics 2022 (SAPs), Pobal Haase-Pratschke Deprivation Index 2022 (HP Deprivation Index), Public Transport Accessibility Levels (PTAL), and Attractions Indices. Section 3.2 details the construction of variables, covering the response variable, offset term and predictors. Section 3.3 addresses data cleaning and variable selection, including procedures for handling missing data, exclusions, and assessment of multi-collinearity. Section 3.4 presents the exploratory data analysis, including descriptive statistics, outlier detection, and diagnostics for overdispersion and zero inflation.

3.1 Data Sources

This section details the primary data sources used in the analysis. Each data source is described below.

3.1.1 Census Small Area Population Statistics (2022)

The core dataset used is the Census 2022 Small Area Population Statistics (SAPS), published by the Central Statistics Office (CSO). Small Areas (SAs) are the lowest level of spatial aggregation used in the Irish census, designed to typically contain between 80 and 120 households, providing fine-grained spatial detail.

The dataset includes detailed information on population structure, household composition, education, employment status, housing conditions, and car ownership, all aggregated to the small area (SA) level (n = 18,919), as illustrated in Figure 3.1.

3.1.2 Pobal HP Deprivation Index (2022)

The Pobal Deprivation Index, which aligns with 2022 Census, is a deprivation index measuring relative deprivation and affluence across all small areas in Ireland. It is widely used for social policy and planning, providing a standardised metric for comparing socio-economic conditions spatially.

The index is constructed using statistical analysis of several census indicators reflecting local socio-economic conditions. These include unemployment, educational attainment, lone parent

Themes	
Theme 1: Sex, Age and Marital Status	Theme 9: Social Class and Socio-Economic Group
Theme 2: Migration, Ethnicity, Religion and Foreign Languages	Theme 10: Education
Theme 3: Irish Language	Theme 11: Commuting , Working from Home and Childcare
Theme 4: Families	Theme 12: Disability, Carers, General Health and Smoking
Theme 5: Private Households	Theme 13: Occupations
Theme 6: Housing	Theme 14: Industries
Theme 7: Volunteers	Theme 15: Motor Car Availability, PC Ownership and Internet Access
Theme 8: Principal Status	

Figure 3.1: Census 2022 Themes

households, age dependency ratio, housing tenure, and population change, among others (Haase and Pratschke 2017).

Scores are standardised with a national mean of 0 and a standard deviation of 10, allowing for consistent comparison across areas and census waves. Negative values indicate higher levels of deprivation, values near zero represent areas close to the national average, and positive values reflect greater affluence.

The Pobal HP Deprivation Index is included in this study as it provides a comprehensive, standardised measure of relative socio-economic advantage and disadvantage at the small area level. Socio-economic deprivation is a well-established predictor of car ownership and transport behaviour, and including the HP Index enables robust control for local contextual effects and facilitates policy-relevant analysis. Descriptive statistics can be viewed in Section 3.4.1.

3.1.3 Public Transport Accessibility Levels

The Public Transport Accessibility Level (PTAL) dataset, developed by the National Transport Authority (NTA), provides a measure of access to public transport services across Ireland. PTAL is a widely used methodology, originally developed by Transport for London and adapted for the Irish context, to quantify how easily residents can access the public transport network from any given location.

Accessibility scores are assigned to a regular grid of 100-metre cells, with each cell's centroid serving as the origin point for analysis. The PTAL score for each cell reflects both the distance to nearby public transport stops and the frequency and reliability of services at those stops (Yadav, Mepparambath, and Patil 2024).

PTAL category construction is based on three main data inputs: a grid of origin points across the study area, a detailed digital map of walkable and cyclable routes, and up-to-date public transport schedules and stop locations from the NTA. For each grid point, the method identifies all public transport stops within a set distance (640m for bus stops and 960m for rail stations) during a specific period such as the morning rush hour. The typical waiting time at each stop is estimated based on service frequency, with an added allowance for variability. These accessibility measures are combined to produce an overall index at each location, which is then categorised into PTAL bands that represent the level of access to public transport.

3.1.4 Attractions Indices

A set of seven "attractions" variables was included to capture the trip-generating potential of each Small Area across a variety of travel purposes. These indices were constructed and shared by the NTA. The indices reflect the destination attractiveness of an area for the following purposes:

1. **Work:** Based on factors such as the number of jobs.

2. **Business-related travel:** Based on factors such as the number of employer's business locations.

3. **Primary education:** Based on factors such as the number of education spaces at the primary level.

4. **Secondary education:** Based on factors such as the number of education spaces at the secondary level.

5. **Tertiary education:** Based on factors such as the number of education spaces at the tertiary level.

6. **Food shopping:** Based on factors such as the number of food retail employees (a proxy for food retail capacity).

7. **Social/leisure/other activities:** Based on factors such as the local population (a proxy for visiting friends and family), leisure, and non-food shopping destinations.

Each attractions variable represents a distinct aspect of land use, service provision, or local amenity that may influence travel demand and household car ownership. The selection and design of these indices align with the principles of destination choice modelling, where accessibility to a range of potential trip destinations is understood to influence travel patterns and mode choice (Board 2025)

3.2 Variable Construction

This section details the derivation and transformation of all variables included in the analysis. The process of variable construction involved identifying the primary outcome (car-free household count), defining the offset term (number of responding households), and constructing the explanatory variables from the census and supplementary datasets. Variables were transformed to ensure comparability across Small Areas. The procedures for handling public transport accessibility scores and attractions/destinations indices are described, alongside the thematic grouping of variables adopted for model development. This approach ensures that all variables are statistically robust.

3.2.1 Response Variable and Offset Term

The outcome variable in this study is the number of households within each Small Area (SA) that reported having no access to a private car. This information is sourced from Census 2022, Theme 15, which captures car availability at the household level for every SA in Ireland.

$$y_i = \text{CarFreeCount}_i = \text{Number of households in area } i \text{ reporting no car ownership}$$

This variable serves as the foundation for all further analysis, representing the observed prevalence of car-free households in each Small Area.
To accompany the primary outcome variable, the number of households in each Small Area that responded to the car ownership question was also recorded:

$$H_i = \text{Number of households in area } i \text{ that responded to the car ownership question}$$

This variable captures the population at risk in each area and was used to ensure that differences in Small Area size and response coverage could be properly accounted for in subsequent analysis.

3.2.2 Census Small Area Population Statistics

A comprehensive set of explanatory variables was derived from the SAPS data to capture relevant socio-economic, demographic, housing, and mobility characteristics at the Small Area (SA) level. As the raw SAPS dataset contains over 800 variables across 15 thematic areas—each stored as absolute counts—pre-processing was required to ensure comparability across SAs of varying population sizes.

To create scale-independent predictors, raw counts were converted to proportions or rates by dividing by appropriate denominators (typically total households or total population). This transformation allows for meaningful comparison between areas, regardless of their underlying population.

Key derived variables include:

- **Socio-demographic proportions**: e.g., proportion of residents aged 20–34, proportion of single-person households, proportion born abroad, etc.
- **Household and housing characteristics**: e.g., average household size, proportion of homeowners, proportion of apartments/flats, proportion with no heating.
- **Employment and education**: e.g., proportion unemployed, proportion with third-level education, proportion of managers/professionals, proportion employed in agriculture.
- **Mobility and accessibility**: e.g., proportion of long-commute residents, proportion who changed address in past year, proportion working from home.

The urban/rural classification was included as a binary indicator for each SA.

Population density was calculated as the total population divided by the area of each Small Area (converted to square kilometres):

$$\text{PopulationDensity}_i = \frac{P_i}{\frac{A_i}{1{,}000{,}000}} = \frac{P_i \times 10^6}{A_i}$$

where:

$$\begin{cases} P_i & = \text{total population in Small Area } i \\ A_i & = \text{area in square metres } (\text{m}^2) \end{cases}$$

Units: persons per km^2

Not all available SAPS variables were included in the final analysis. Variable selection was guided by theoretical relevance, preliminary correlation analysis, and checks for multicollinearity (see Section 3.4.2). This approach ensured the explanatory variables included in the final model were both statistically robust and substantively meaningful for understanding car-free household patterns in Ireland.

3.2.3 Public Transport Accessibility Scores

Public Transport Accessibility Level (PTAL) scores were spatially mapped to Census Small Areas (SAs) to provide an small area level measure of public transport accessibility.

The PTAL data was stored as vector polygons, representing a $100\,\text{m}^2$ grid cell, with an assigned accessibility category for each grid cell. A spatial join was performed between the PTAL polygons and census SA boundaries, ensuring a both datasets were projected to the Irish Transverse Mercator (ITM) common coordinate reference system (CRS) to confirm compatibility. Each SA typically intersected multiple PTAL polygons, therefore to summarise accessibility at the SA level, the modal PTAL category was assigned to each area. This approach is intended to capture the dominant level of service experienced by residents within each SA.

A number of rural SAs did not intersect with any PTAL polygons, due to lack of any public transport availability. These were assigned a "No Service" category to reflect the absence of public transport options. The resulting PTAL variable was treated as a categorical indicator of public transport accessibility in all subsequent analyses. Descriptive statistics can be viewed in Section 3.4.1.

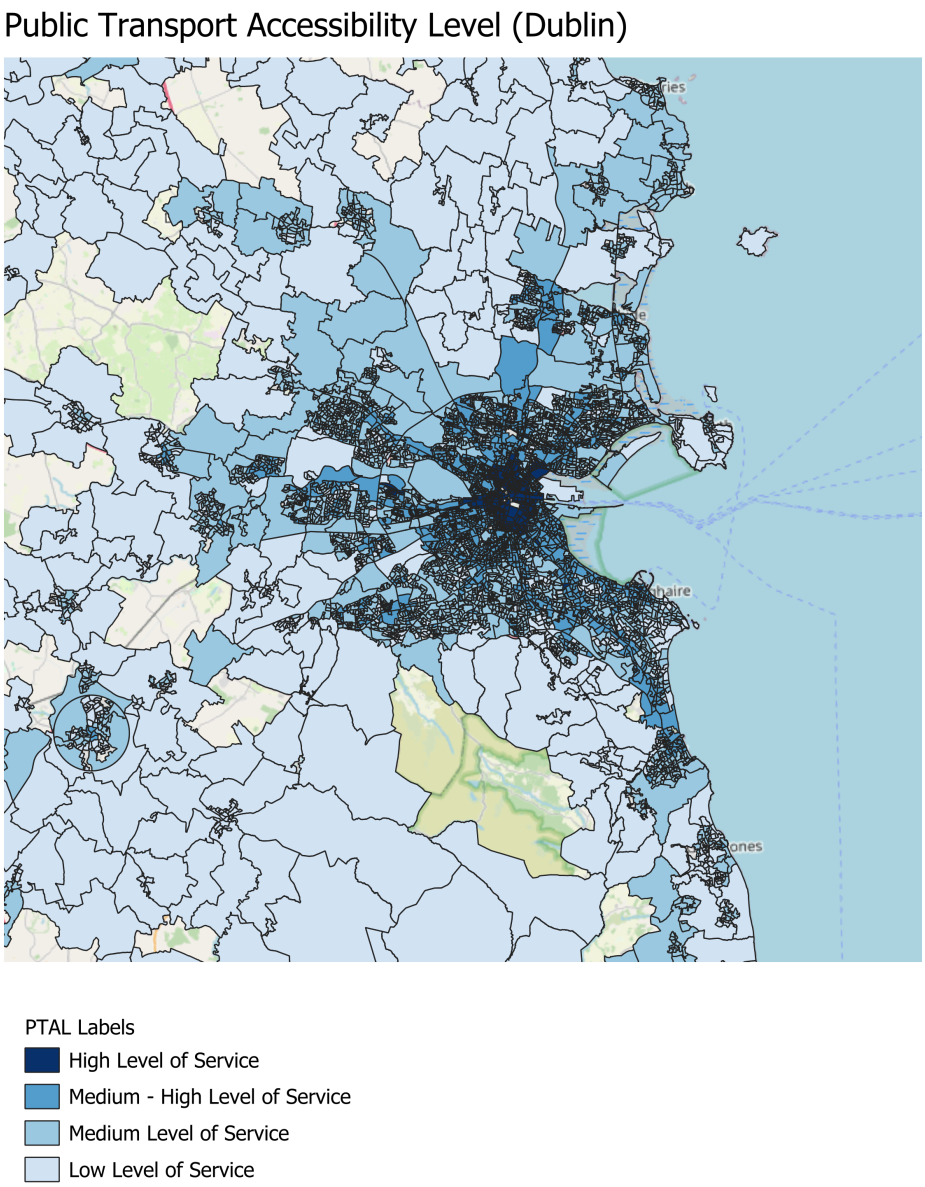

Figure 3.2: Example PTAL Level of Service Map: Dublin

3.2.4 Attractions/Destinations Indices

The seven Attractions/Destinations indices described in Section 3.1.4 were further transformed to improve their suitability for regression modelling and interpretability.

- **Log Transformation:** All seven indices—work, primary education, secondary education, tertiary education, social/leisure, food shopping, and friends/family—were log-transformed using $\log(1 + x)$ to compress extreme high values, better linearise their relationship with the outcome, and handle multiplicative effects.

- **Binary Indicators for Education Indices:** For the three education indices (primary, secondary, tertiary), binary variables were created to indicate the presence (> 0) or absence ($= 0$) of local education accessibility in each Small Area.

- **Scaling of Non-Education Indices:** The log-transformed non-education indices (work, social/leisure, food shopping, friends/family) were standardised (mean zero, unit variance) to facilitate comparability of coefficients and improve model convergence.

These transformations were applied to reduce the influence of outliers, meet the assumptions of linearity in regression, and ensure that variables entered the model on a consistent scale. All processed versions of the indices were considered in variable selection and model building.

3.3 Data Cleaning and Variable Selection

3.3.1 Missing Data and Exclusions

To ensure robust and reliable analysis, a systematic approach to data cleaning was implemented prior to variable construction and modelling. Each stage of the cleaning process was designed to minimise bias and instability, resulting in a dataset that accurately reflects underlying population characteristics across all small areas. The cleaning steps described in this section address completeness, response rates, and the exclusion of anomalous or sparse areas. The outcome of this process provides reliable dataset for subsequent modelling and inference.

Assessment of Completeness All base datasets were checked for completeness and internal consistency. No missing data were identified in any of these datasets prior to processing. All files provided full national coverage, allowing for robust small-area analysis once merged at the Small Area (SA) level.

Calculation of Response Rates To safeguard against bias from incomplete census responses, a response rate variable was constructed for each Small Area. This measured the proportion of households that provided a valid answer to the car ownership question (Theme 15), with non-stated responses excluded from both numerator and denominator. SAs with low response rates can produce unreliable estimates, increasing the risk of instability or bias.

A minimum response threshold of 30% was applied, in line with accepted practice for small-area research. SAs falling below this cut-off were excluded from further analysis.

Exclusion of Anomalous and Sparse Areas Additional cleaning steps targeted SAs with characteristics that could undermine robust analysis:

- **Zero-household SAs:** Three urban SAs were removed as they reported zero households, resulting in zero values for most census-derived variables. These areas do not provide usable data for household-level analysis.

- **Very small population SAs:** Two SAs with fewer than 20 households were excluded to minimise instability in rate calculations; such small bases can unduly influence results.

- **Post-processing missing values:** Two further records with missing values were detected after calculating proportion variables (likely due to denominator or join issues) and were removed.

In total, these exclusions represented only 0.1% of the initial dataset ($n = 25$ of $18,919$ SAs). The resulting cleaned dataset comprised $n = 18,894$ SAs, retaining the full heterogeneity of Ireland's small areas. After these cleaning steps were completed the census SAPS dataset was merged with the Pobal HP Deprivation Index, Public Transport Acessibility Levels, and the Attractions Indices, ensuring that only robust, high-quality cases contributed to the final dataset.

Table 3.1: Summary of Small Areas Excluded During Cleaning

Exclusion Criterion	**n**	**Notes**
<30% response to car ownership question	18	Low reliability (Theme 15)
Zero households reported (urban areas)	3	Empty values
<20 households reported	2	Too few households for stability
Missing values	2	NA after proportion derivation
Total excluded	**25**	∼0.1% of dataset

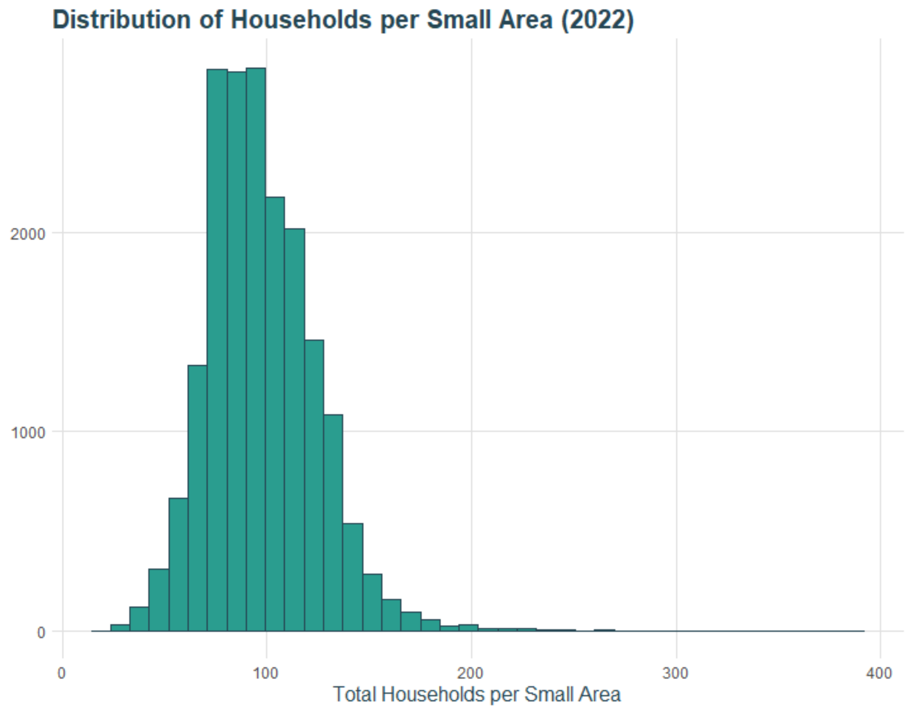

Figure 3.3: Distribution of Household Count after Data Cleaning

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Value	21.00	79.00	94.00	97.33	113.00	390.00

Table 3.2: Summary of Household Count after Data Cleaning

3.3.2 Multicollinearity and Variable Selection

Diagnostic checks were carried out to identify and address multicollinearity. This was necessary to ensure statistical stability in the model and to support accurate interpretation of coefficients. Strong correlations between explanatory variables can inflate standard errors, introduce redundancy, and make it difficult to isolate the contribution of individual factors. 38 predictor variables were included in variable selection analysis, these are listed in table A.1 in appendix A.

To evaluate relationships, a pairwise correlation matrix was generated. Variables showing high correlations (above 0.7) were flagged for review. Variance inflation factors (VIFs) were also calculated using a linear regression model. A threshold of 5 was applied to identify predictors whose variance was likely inflated due to collinearity with other inputs.

Variables were excluded (n=9) if they exceeded the pairwise correlation or VIF threshold. The final set of explanatory variables demonstrated acceptable levels of correlation and variance inflation, and was judged to provide a statistically stable and theoretically meaningful basis for modelling. Removed variables are listed in table 3.3 below.

Sociodemographic Effects
Prop. One Person HH
Prop. Multi-Family Units
Prop. Couple with Children
Avg. Family Size
Socioeconomic Effects
Prop. No or Primary Educ.
Prop. Unemployed
Built Environment
Prop. Homeowners
Public Transport and Destination Accessibility
Employer/Business Attr.
Prop. Work from Home

Table 3.3: Variables excluded after pairwise correlation and VIF analysis

Figure **??** displays a correlation matrix of all candidate predictor variables included in the analysis. Each cell shows the pairwise correlation coefficient between two variables, with the colour scale ranging from green (strong negative correlation, -1) to pink (strong positive correlation, +1). Lighter colours indicate weaker or no correlation. This plot provides an overview of the relationships between predictors and is was to identify highly correlated variables that could introduce multicollinearity into the model.

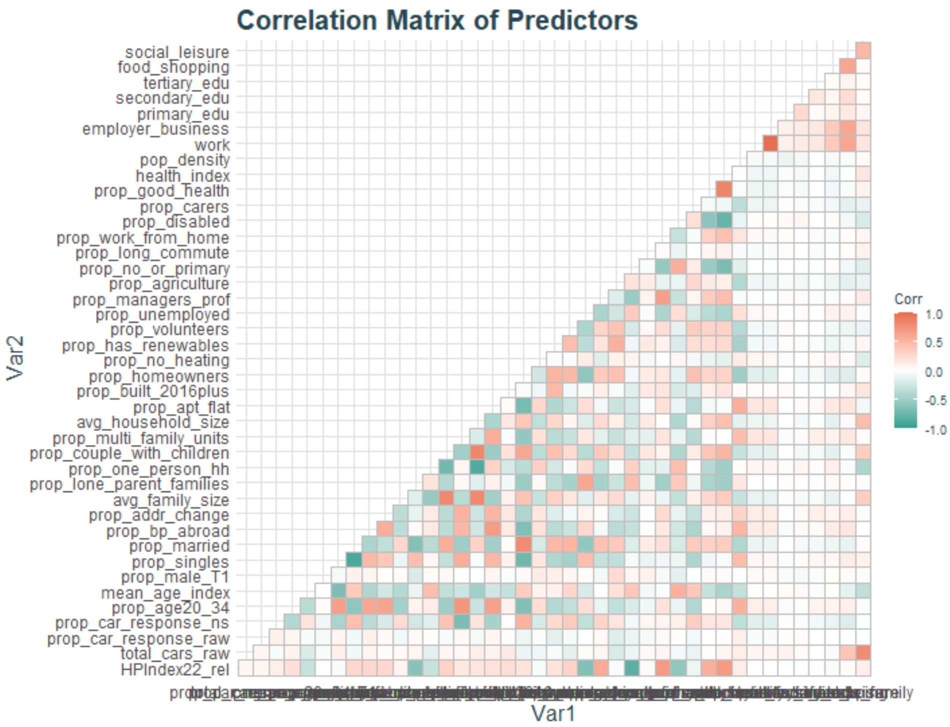

Figure 3.4: Correlation Matrix

3.4 Exploratory Data Analysis

3.4.1 Descriptive Statistics

Descriptive statistics are reported for 18,894 small areas, for 27 predictor variables and the outcome variable car-free-count.

Predictor Variables

The predictor variables are grouped into four main conceptual themes: Sociodemographic Effects, Socioeconomic Effects, Built Environment, and Public Transport and Destination Accessibility. This thematic structure follows established practice in the car ownership and spatial analysis literature (e.g., Eakins, 2013; Cervero & Murakami, 2010), where researchers typically distinguish between individual or household characteristics, socioeconomic context, aspects of the built environment, and measures of transport and destination accessibility. Grouping variables in this way facilitates both interpretation and comparison with prior studies, and allows for a clearer understanding of how different themes jointly influence car-free household rates.

Table 3.4 summarises the number of small areas (SAs) classified as urban or rural in the sample. The CSO employs an urban/rural classification based on population density and patterns of residents' employment locations.

Table 3.4: Count of urban and rural areas in the analytic sample

Classification	Count
Urban	13,160
Rural	5,734

Table 3.5 summarises the distribution of small areas across Public Transport Accessibility Level (PTAL) categories. PTAL is an index reflecting the ease of access to public transport services in each area, ranging from "No Service" to "High Level of Service". Figure 3.5 presents a sample map of Dublin showing the PTAL category for small area.

Table 3.5: Distribution of Public Transport Accessibility Level (PTAL) categories

PTAL Category	**Count**
No Service	4,097
Low Level of Service	8,115
Medium Level of Service	4,044
Medium-High Level of Service	2,049
High Level of Service	589

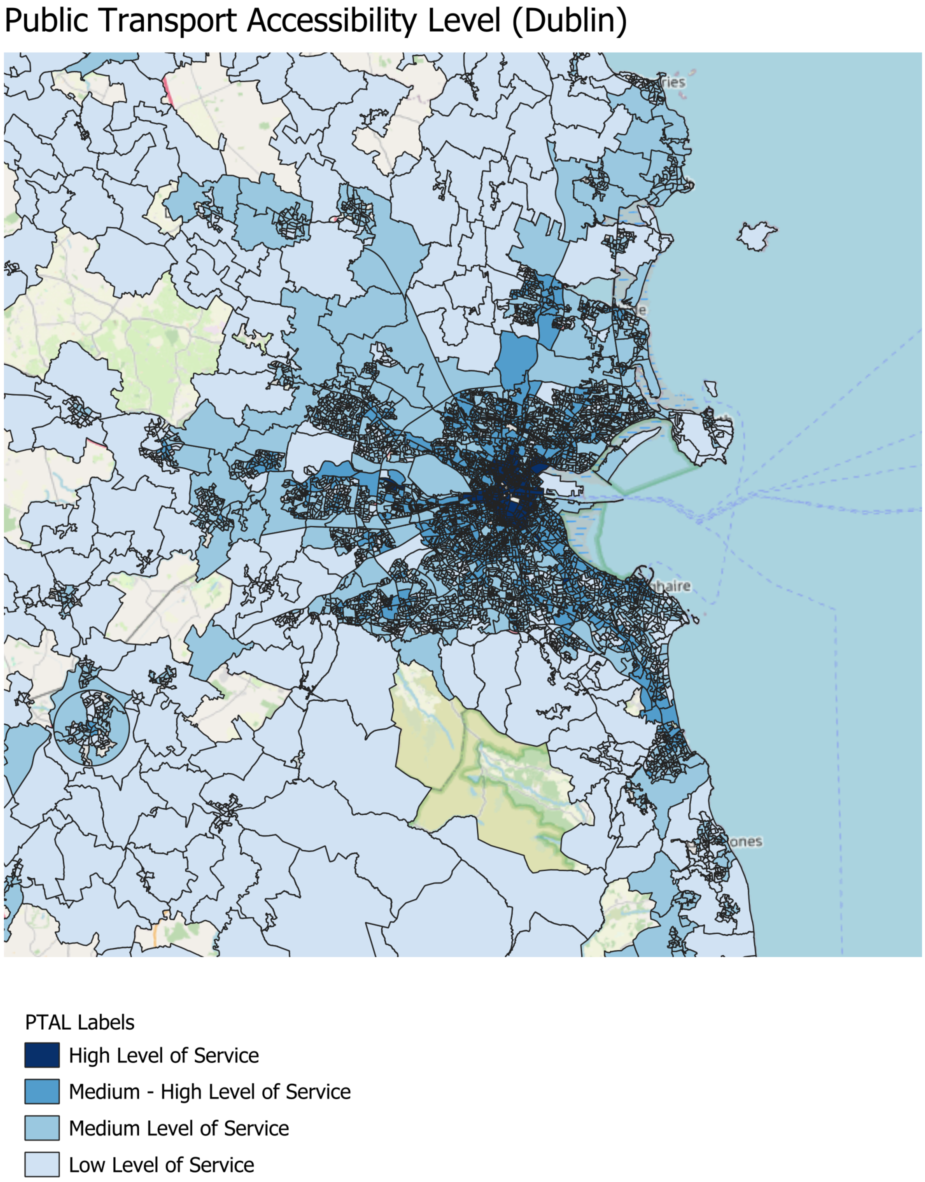

Figure 3.5: Example PTAL Level of Service Map: Dublin

Table 3.6 presents descriptive statistics for the continuous and count predictor variables.

Table 3.6: Summary statistics for continuous and count predictors

Predictor	**Min**	**Q1**	**Median**	**Mean**	**Q3**	**Max**
Sociodemographic Effects						
Deprivation Index	-56.14	-5.60	1.04	0.00	6.75	29.37
Prop. Age 20–34	0.01	0.13	0.16	0.18	0.20	0.82
Prop. Male	0.28	0.47	0.49	0.49	0.51	0.86
Prop. Born Abroad	0.01	0.11	0.16	0.20	0.25	0.84
Prop. Addr. Change	0.00	0.01	0.02	0.03	0.04	0.61
Avg. HH Size	1.06	2.46	2.75	2.73	3.01	4.41
Prop. Lone Parent	0.00	0.10	0.15	0.17	0.22	1.00
Prop. Disabled	0.04	0.18	0.21	0.22	0.26	0.72
Prop. Carers	0.00	0.04	0.06	0.06	0.07	0.20
Prop. Good Health	0.75	0.97	0.98	0.98	0.99	1.00
Prop. Volunteers	0.01	0.10	0.14	0.14	0.17	0.48
Prop. Managers/Prof.	0.00	0.09	0.13	0.14	0.18	0.55
Socioeconomic Effects						
Prop. Built 2016+	0.00	0.00	0.01	0.05	0.04	1.00
Prop. No Heating	0.00	0.00	0.01	0.01	0.02	0.15
Prop. Renewables	0.00	0.10	0.21	0.25	0.39	1.00
Prop. Agriculture	0.00	0.00	0.01	0.05	0.07	0.57
Prop. Long Commute	0.00	0.06	0.09	0.09	0.13	0.44
Built Environment						
Pop. Density	0.53	45.86	2014.09	3805.14	5400.03	103703.70
Attractiveness Indices						
Food Shopping Attr.	0.00	0.00	0.00	25.78	13.64	3391.77
Social/Leisure Attr.	21.78	89.27	112.84	128.05	144.51	2919.92
Work Attr.	0.00	2.63	13.13	71.00	46.38	11185.19
Primary Edu. Attr.	0.00	0.00	0.00	22.83	2.44	1225.93
Secondary Edu. Attr.	0.00	0.00	0.00	19.24	0.00	1978.03
Tertiary Edu. Attr.	0.00	0.00	0.00	10.04	0.00	21768.95

Table 3.7 presents the standard deviations (SDs) for the raw values of all continuous and count predictor variables included in the analysis, grouped by conceptual theme. Reporting these values facilitates interpretation of model results, as regression effects are expressed per one SD increase in each predictor. Including SDs for all predictors enhances the transparency and reproducibility of the analysis, enabling readers to assess the real-world scale of a one-standard-deviation change in each variable.

Table 3.7: Standard deviations (SD) for raw values of continuous and count predictors, grouped by theme.

Predictor	**SD**
Sociodemographic Effects	
Prop. Age 20–34	0.09
Prop. Male	0.03
Prop. Born Abroad	0.13
Prop. Addr. Change	0.04
Avg. HH Size	0.42
Prop. Lone Parent	0.10
Prop. Volunteers	0.05
Prop. Disabled	0.06
Prop. Carers	0.02
Prop. Good Health	0.02
Socioeconomic Effects	
Deprivation Index	10.00
Prop. No Heating	0.02
Prop. Managers/Prof.	0.08
Prop. Agriculture	0.07
Built Environment	
Prop. Built 2016+	0.13
Prop. Renewables	0.18
Pop. Density	5890.42
Public Transport and Area Attractiveness	
Prop. Long Commute	0.05
Food Shopping Attr.	111.79
Social/Leisure Attr.	82.95
Work Attr.	294.43
Primary Edu. Attr.	79.16
Secondary Edu. Attr.	110.35
Tertiary Edu. Attr.	261.61

Outcome Variable: Car-Free Households

Table 3.8 and Figure 3.6 summarise and illustrate the distribution of the outcome variable, car-free household count. The distribution is right-skewed with a long tail of higher values. The standard deviation (14.21) substantially exceeds the mean (12.97), indicating overdispersion. These descriptive patterns motivated the subsequent diagnostic checks for outliers, overdispersion, zero-inflation. These steps aimed to ensure that model assumptions were not violated and that the chosen error structure could adequately account for observed data patterns, including outliers, overdispersion and excess zeros.

Table 3.8: Summary statistics for car-free household count (outcome variable)

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
0	3	7	12.97	18	180	14.21

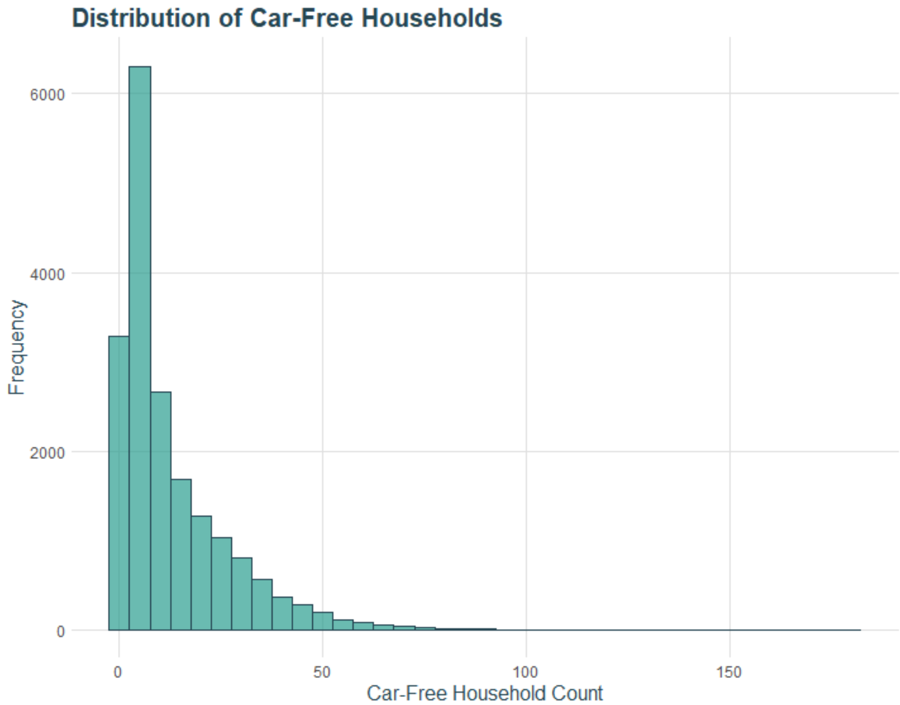

Figure 3.6: Distribution of Car-Free Household Counts

3.4.2 Outlier Detection

To assess the influence of extreme values on the outcome distribution, outlier detection was conducted. Particular attention was given to the count of car-free households, given its central role in the modelling framework and its potential sensitivity to local anomalies in small-area data.

The primary method involved fitting a negative binomial model with an intercept-only specification and estimating the probability of observing each count under the fitted distribution. Observations with a tail probability below 0.01 were flagged as statistical outliers. A total of 258 areas were identified as outliers, representing approximately 1.4% of the dataset. Outlier values were examined in relation to several key characteristics, including population density, deprivation, and age structure. The flagged areas were predominantly located in urban settings and were more likely to fall within zones of high or medium-high public transport accessibility, as measured by the Public Transport Accessibility Level (PTAL) index.

No evidence of data errors or implausible values was found during these reviews. The outliers appeared to reflect real spatial variation in car ownership patterns. All observations were retained for analysis, with the understanding that they represent legitimate variation rather than data errors or anomalies.

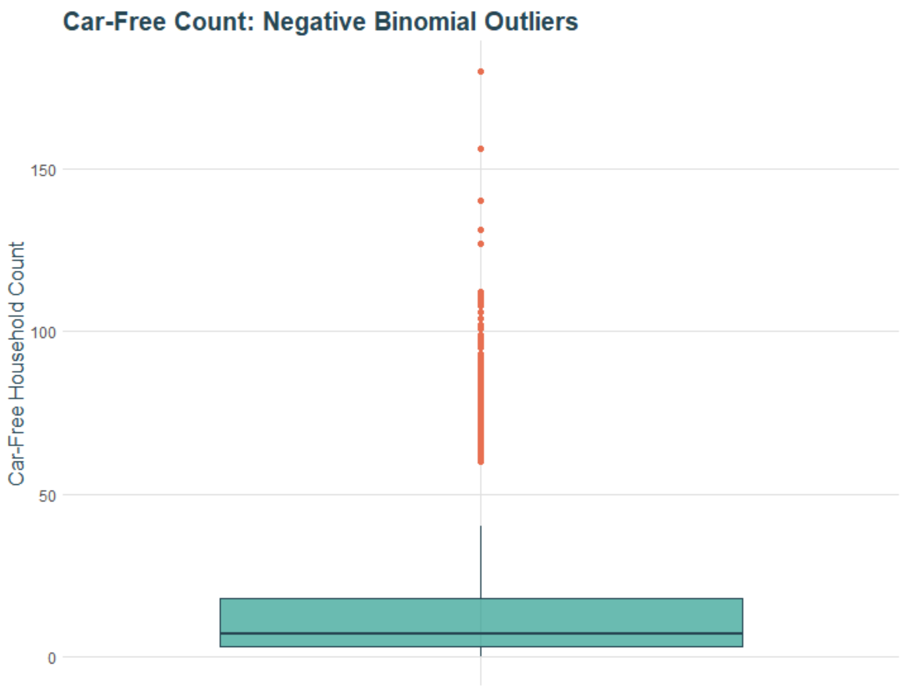

Figure 3.7: Car Free Count - Outliers

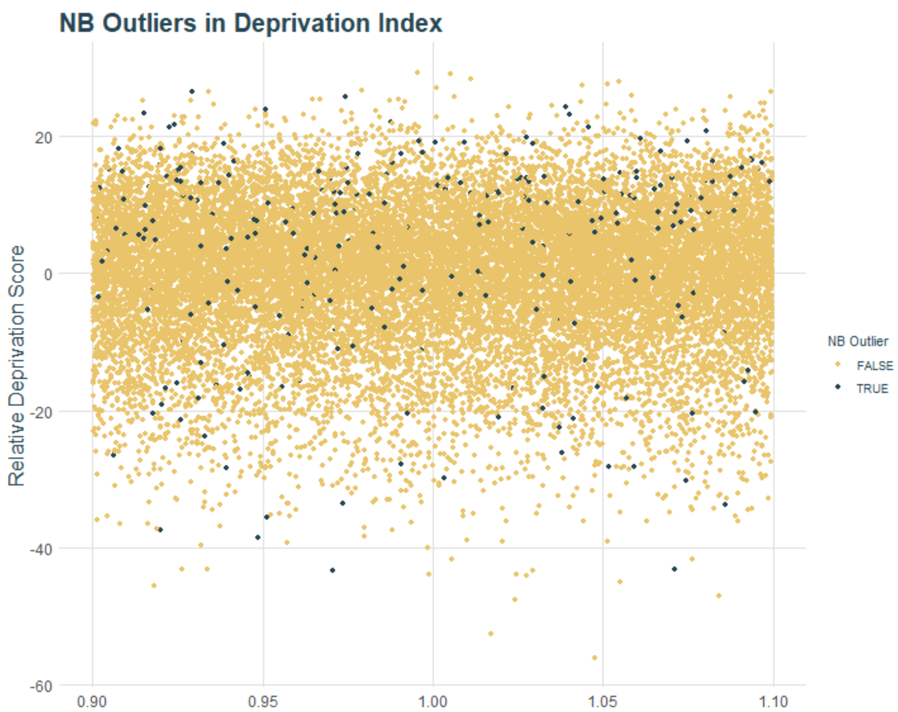

Figure 3.8: No Pattern Found in Car Free Outliers

3.4.3 Overdispersion

Overdispersion was formally tested using the Pearson chi-squared statistic from a Poisson model, where the residual deviance was compared to the residual degrees of freedom. The resulting dispersion ratio was substantially greater than one, providing strong evidence that the Poisson assumption of equal mean and variance was violated.

Statistic	Poisson	Negative Binomial
Pearson Chi-square	86,023.10	19,795.69
Dispersion	4.55	1.05

Table 3.9: Model comparison statistics for Poisson and Negative Binomial models

Residual diagnostics further supported this conclusion. Plots of Pearson residuals against fitted values showed a characteristic funnel shape under the Poisson specification, indicating non-constant variance. Quantile–quantile plots also revealed heavy tails. In contrast, a negative binomial model demonstrated improved residual behaviour, with more homoscedastic residuals and a distribution that more closely followed theoretical expectations.

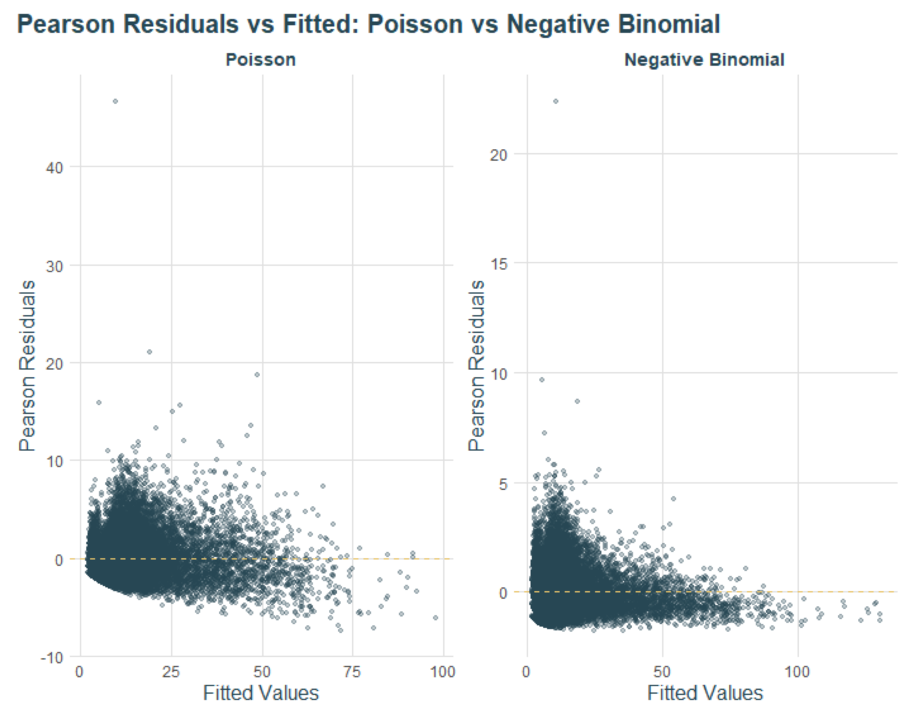

Figure 3.9: Residuals vs Fitted: Poisson vs NB

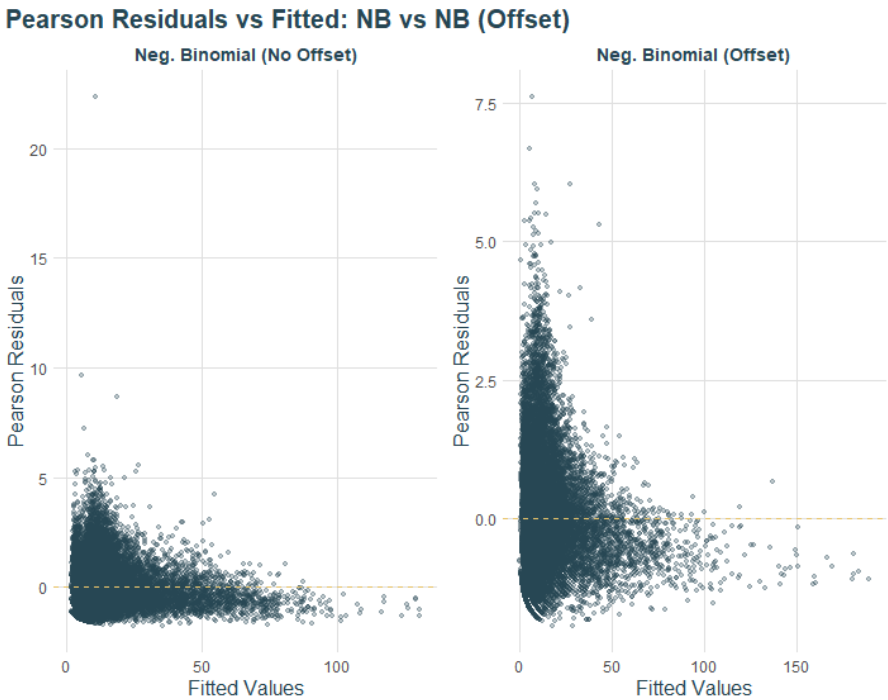

Figure 3.10: Residuals vs Fitted: NB vs NB with offset

3.4.4 Zero Inflation

To assess whether the data exhibited zero-inflation, the proportion of zero responses in the dataset was compared to the expected proportion under a baseline negative binomial model. The observed frequency of zeros did not exceed expectations, indicating that a zero-inflated model was not required.

Statistic	**Value**
Observed proportion of zeros	0.03
Expected proportion of zeros	0.06

Table 3.10: Observed vs. expected proportion of zero counts

Chapter 4

Methodology

This chapter outlines the statistical approach and modelling framework adopted for the analysis of car-free households in Ireland. The methodology is organised as follows. Section 4.1 provides an overview of the general statistical approach, including the specification of the main regression model. Section 4.2 introduces the Bayesian framework and the use of Integrated Nested Laplace Approximation (INLA) for model estimation, with discussion of priors and hyperparameters. Section 4.3 details the spatial modelling strategy, covering both the Besag–York–Mollié 2 (BYM2) spatial model and the definition of spatial units, adjacency, and neighbourhood structure. Section 4.4 addresses the modelling of urban–rural heterogeneity. Section 4.5 discusses model selection procedures, and Section 4.6 outlines the approach to interpreting model effects. This structured methodology provides the basis for the subsequent presentation and interpretation of results.

4.1 Overview of Statistical Approach

This study uses a Bayesian spatial negative binomial regression to model the count of car-free households per Small Area (SA) in Ireland, accounting for overdispersion, spatial autocorrelation, and urban–rural heterogeneity. Models are implemented using the INLA package in R.

Overdispersion in the response variable (see Section 3.4) motivates use of a negative binomial distribution. Spatial autocorrelation, identified in exploratory analysis, justifies spatial random effects. Interactions with urban–rural classification are included to capture context-specific effects.

4.1.1 Model Specification

Model formulation:

$$\log(\mu_i) = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \sum_{j=1}^{p} \gamma_j (x_{ij} \times \text{Rural}_i) + b_i + \log(\text{Households}_i) \tag{4.1}$$

where:

- μ_i — the expected number of car-free households in Small Area i;
- x_{ij} — predictor j in area i, covering socio-economic, demographic, housing, and accessibility characteristics;
- β_j — the main effect of predictor x_j, interpreted as the effect in **urban areas** (urban is the reference category);

- γ_j — the interaction effect, quantifying how the effect of predictor x_j differs in **rural** areas compared to urban;
- Rural_i — a binary indicator variable, taking the value 1 for rural areas and 0 for urban;
- b_i — a spatially structured and unstructured random effect following the BYM2 formulation, capturing residual spatial dependence;
- $\log(\text{Households}_i)$ — an offset term accounting for the total number of households, thereby modelling a **rate of car-free households**.

Negative Binomial Model The Negative Binomial (NB) distribution is an extension of the Poisson distribution that includes a dispersion parameter to account for overdispersion—where the variance exceeds the mean. This makes it suitable for count data such as the number of car-free households per Small Area (SA).

Formally, the NB model is specified as:

$$y_i \sim \text{NB}(\mu_i, \theta)$$

where:

- μ_i is the expected count for SA i,
- θ is the dispersion parameter (smaller values indicate greater overdispersion).

The variance of y_i is given by:

$$\text{Var}(y_i) = \mu_i + \frac{\mu_i^2}{\theta}$$

The expected value μ_i is linked to covariates via a log-linear function:

$$\log(\mu_i) = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} + \log(\text{offset}_i)$$

where the offset is the total number of households per SA.

4.2 Bayesian Inference and INLA

4.2.1 Why Bayesian?

Bayesian spatial models offer a powerful way to analyse geographically structured data. Unlike traditional statistical models that produce single-point estimates, Bayesian approaches provide full probability distributions for each parameter, which allows for a richer expression of uncertainty. They also allow researchers to incorporate prior knowledge about parameters, if such information is available.

4.2.2 INLA Overview

To fit the spatial model, the Integrated Nested Laplace Approximation (INLA) method was used. INLA is an efficient and accurate alternative to Markov Chain Monte Carlo (MCMC) methods for a class of models known as latent Gaussian models. INLA works particularly well when the model includes complex structures like spatial or temporal random effects, and is well suited for large datasets. In this case, the INLA framework was used to fit a spatial negative binomial regression model.

4.2.3 Priors and Hyperparameters

All continuous predictor variables were standardised to mean zero and unit variance to improve model stability and interpretability. Log transformations were applied to the attractions indices to address skewness. Categorical predictors were coded as factors.

The following priors and hyperparameters were used in the Bayesian spatial negative binomial model:

- **Fixed effects (β_j):** Standard Normal prior, $\mathcal{N}(0, 1)$, was used for all continuous predictors. This weakly informative prior helps constrain unreasonable effect sizes without strongly influencing estimates.

- **Intercept (β_0):** Diffuse Normal prior, $\mathcal{N}(0, 10^4)$, to avoid undue influence on baseline estimates.

- **Overdispersion parameter (θ):** Penalised complexity (PC) prior was placed on the standard deviation scale ($\sigma = 1/\sqrt{\theta}$), with $P(\sigma > 1) = 0.25$, reflecting moderate uncertainty about overdispersion.

- **Spatial random effects (BYM2):**

  - *Precision prior:* PC prior with $P(\sigma_{\text{spatial}} > 1) = 0.01$, penalising overly complex spatial patterns.
  - *Mixing parameter (ϕ):* PC prior with $P(\phi > 0.5) = 2/3$, reflecting a preference for moderate spatial structure but remaining data-driven.

All priors were chosen to be weakly or moderately informative, in line with best practice for spatial Bayesian models. Posterior means and 95% credible intervals were extracted for all model parameters. The posterior distribution of ϕ was used to assess the proportion of residual spatial variance that was spatially structured (i.e., due to similarity among neighbouring areas) versus unstructured (random noise).

4.3 Spatial Modelling

4.3.1 Besag–York–Mollié 2 (BYM2) Spatial Model

To capture spatially structured and unstructured variation, the Besag–York–Mollié 2 (BYM2) model (Riebler et al., 2016) was used for spatial random effects. The BYM2 model expresses the spatial random effect for area i as:

$$w_i = \sqrt{\frac{\phi}{\tau}} u_i^* + \sqrt{\frac{1-\phi}{\tau}} v_i$$

where u_i^* is the structured (ICAR) component capturing spatial clustering, v_i is the unstructured noise, ϕ ($0 \leq \phi \leq 1$) controls the proportion of structured variation, and τ is overall precision. Adjacency is defined by the Queen rule as above.

The mixing parameter ϕ is interpreted as the proportion of spatial variation explained by clustering among neighbouring areas; τ determines the total variance. Posterior inference on ϕ allows quantification of the degree of spatial clustering.

Including a spatial random effect via the BYM2 specification allows the model to account for unmeasured geographic factors and smooth estimated rates based on information from neighbouring areas. The spatial random effect can be mapped to visualise residual geographic patterns in car-free household prevalence, providing insight into unobserved spatial heterogeneity.

Justification Spatial autocorrelation—whereby geographically proximate areas tend to have similar rates of car-free households—was evident in exploratory analysis. If ignored, this spatial structure can bias statistical inference and mask local clustering. Including spatial effects in the model accounts for these dependencies and improves model fit, as shown by substantial reductions in DIC and WAIC (Table 4.1).

Table 4.1: Model Evaluation Metrics: Socio-Demographic vs Spatial (BYM2) Models

Metric	**Socio-Demographic Model**	**Spatial BYM2 Model**
DIC	112,321.8	105,755.0
WAIC	112,323.7	105,906.2
Mean log-CPO	−2.9725	−2.812
Phi (structured spatial proportion)	—	0.458

Inclusion of spatial effects (BYM2) improved model fit relative to a socio-demographic-only model, with a ϕ estimate of 0.458 indicating that approximately 46% of residual variance is spatially structured—confirming the importance of spatial clustering in car-free household patterns.

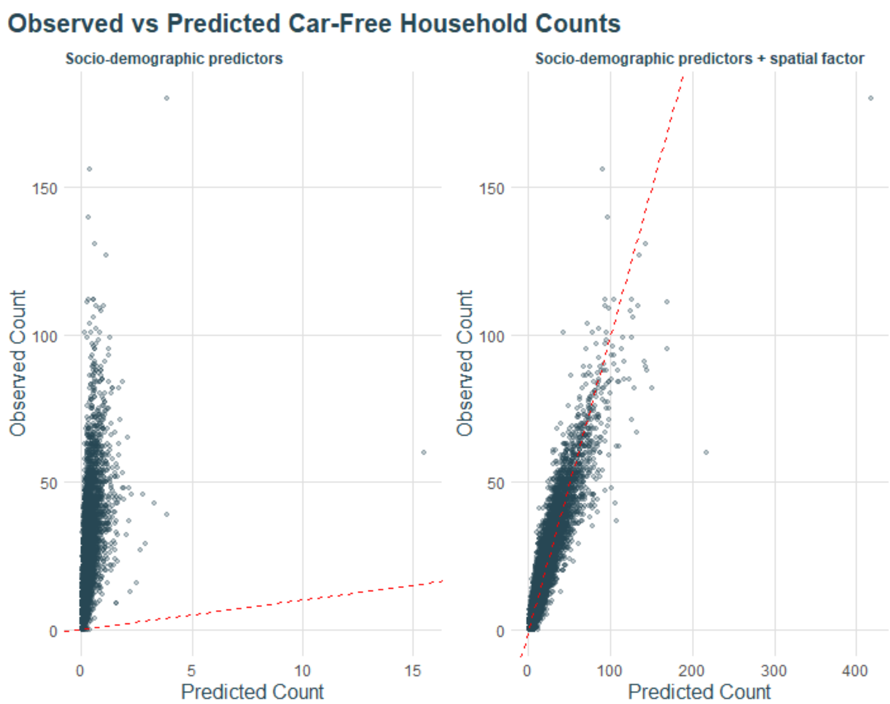

Figure 4.1: Observed vs Predicted Car-Free Household Counts

4.3.2 Spatial Units, Adjacency, and Neighbourhood Structure

The spatial units of analysis in this study are Census Small Areas (SAs), which are the smallest standard geographic divisions used for national statistics in Ireland. Each SA is a discrete, non-overlapping polygon representing a local community, with a typical population of 80 to 120 households. The final analytic sample includes 18,894 SAs, each with associated demographic, socio-economic, and transport characteristics.

Spatial relationships between areas were formalised using a first-order Queen contiguity rule. Under this rule, two SAs are considered neighbours if they share either a boundary (edge) or a vertex (corner) on the map. This results in a more inclusive neighbourhood structure than Rook contiguity, which considers only shared boundaries. The complete set of these neighbour relationships is captured in an adjacency matrix W, where each element w_{ij} equals 1 if areas i and j are neighbours, and 0 otherwise.

This neighbourhood structure, defined by the adjacency matrix, underpins all spatial modelling in this analysis. It is used to specify which areas are considered linked in the spatial random effect model, ensuring that spatial dependence is accurately accounted for in the estimation of model parameters.

4.4 Modelling Urban-Rural Heterogeneity

Urban and rural areas in Ireland differ markedly in transport infrastructure, land use, service availability, and socio-economic conditions. Prior research highlights that the factors associated with car ownership behaviour often operate differently across these contexts. To ensure the analysis accurately captures this heterogeneity, and to avoid masking meaningful subgroup effects, interaction terms were included between all predictors and a binary indicator for rural classification (based on the CSO's 2022 small area typology).

Urban areas served as the reference category for all factor contrasts. In this specification, each coefficient represents the estimated effect of a predictor in urban areas, while the corresponding interaction term quantifies how that effect differs in rural areas. The effect for rural areas is calculated as the sum of the urban coefficient and the interaction (rural difference) coefficient.

Formally, for each predictor x_j, the model includes a main effect β_j (for urban areas) and an interaction effect γ_j (difference for rural areas), such that the total effect in rural areas is $\beta_j + \gamma_j$.

This approach facilitates nuanced interpretation of how socio-demographic, housing, and transport-related factors may operate differently depending on geographic context. For example, the influence of public transport accessibility or built form may be amplified or attenuated in rural areas compared to urban. The model retains the structured spatial component via the BYM2 specification, allowing spatially correlated variation to be estimated across all small areas while simultaneously modelling urban/rural heterogeneity.

4.5 Model Selection

Model comparison and selection were guided by two Bayesian information criteria:

- **Deviance Information Criterion (DIC):** A generalisation of AIC for Bayesian models, DIC evaluates the trade-off between model fit and complexity. Lower DIC values indicate a better-fitting, more parsimonious model.

- **Widely Applicable Information Criterion (WAIC):** WAIC estimates out-of-sample predictive performance, penalising complexity. As with DIC, lower WAIC values denote improved fit.

These indices were used to compare alternative model specifications, with preference given to models achieving the lowest DIC and WAIC scores. Table 4.2 summarises the comparison of baseline, spatial, and spatial interaction models. Δ values are relative to the model in the row above.

Adding spatial random effects (BYM2) to the baseline model reduced WAIC by 239 points and DIC by 277 points, demonstrating substantially improved fit. Incorporating urban–rural interaction terms provided an additional reduction of 169 WAIC points and 168 DIC points relative to the spatial-only model. These results strongly support the inclusion of both spatial structure and urban–rural heterogeneity in modelling car-free household counts across Ireland.

Table 4.2: Model comparison using WAIC and DIC

Model	**WAIC**	**DIC**	**Δ WAIC**	**Δ DIC**
Baseline (no spatial, no interaction)	104,312	104,308	0	0
Spatial (BYM2, no interaction)	104,073	104,031	-239	-277
Spatial + Interaction (BYM2)	103,904	103,863	-169	-168

Overall, both DIC and WAIC indicate that explicitly modelling spatial dependence and urban–rural differences provides a more accurate and explanatory account of the geographic distribution of car-free households.

4.6 Interpretation of Model Effects

Model results are reported as posterior means and 95% credible intervals (CrIs), separately for urban and rural areas. For each predictor, incidence rate ratios (IRRs) and corresponding percentage changes in the expected count of car-free households are also presented to aid interpretation. In Bayesian analysis, a 95% CrI represents the range within which the true parameter value lies with 95% probability, given the observed data and model assumptions. This contrasts with frequentist confidence intervals, as CrIs allow direct probability statements about parameters. The IRR represents the multiplicative effect of a specified increase in each predictor, and the percentage change expresses how much the expected count of car-free households increases or decreases for each specified increment in the predictor.

Model Coefficients

The negative binomial model relates predictors to the expected count outcome using a log link function. This means that each coefficient (β) represents the change in the *logarithm* of the expected count of car-free households for a one-unit increase in the predictor, holding other variables constant:

$$\log(\mathrm{E}[Y|X]) = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p$$

A one-unit increase in a predictor leads to a proportional change in the expected count, specifically:

$$\frac{\partial \mathrm{E}[Y|X]}{\partial X_j} = \mathrm{E}[Y|X] \times \beta_j$$

To aid interpretation, coefficients are exponentiated to yield incidence rate ratios (IRRs), which give the multiplicative effect of an increase in the predictor.:

$$\mathrm{IRR} = \exp(\beta \times \text{Increment})$$

The expected percentage change in the outcome for an increment is calculated as:

$$\% \text{ Change} = (\text{IRR} - 1) \times 100$$

For example, an IRR of 1.12 means a one-unit increase in the predictor is associated with a 12% increase in the expected count.

Increments

The increment for each variable is chosen to provide effect estimates. For proportion variables (e.g., proportion aged 20–34), effects are interpreted per 10 percentage point increase. For continuous predictors that were standardised (e.g., deprivation index), effects are interpreted per one standard deviation increase in the original variable. For count-based accessibility variables, effects are interpreted either per one standard deviation increase in the log-transformed count of facilities (where the variable was log-transformed and scaled, e.g. food shopping), or as the difference between areas with and without access (where the variable was converted to a binary indicator, e.g. primary education). Their effects are thus interpreted as the difference between areas with and without access. The PTAL variable, representing public transport accessibility, was included as a categorical factor with "No Service" as the baseline; coefficients for other PTAL levels are interpreted relative to this reference. These increments are listed in table 4.3.

Main and Interaction Effects

Urban–rural differences were estimated using interaction terms. Main effects represent associations in urban areas (the reference group), while interaction terms show how these associations differ in rural areas. The total effect in rural areas is the sum of the main (urban) effect and the corresponding interaction term.

Effect / Predictor Type	**Interpretation**
Main effect	Association in urban areas (reference group)
Interaction effect	Difference in association for rural areas relative to urban
Total effect in rural areas	Sum of main (urban) effect and interaction coefficient
Proportion-based predictors	Per 10 percentage point increase
Standardised predictors	Per one standard deviation increase in the original variable
Log-transformed and scaled predictors	Per one standard deviation increase in the log-transformed count
Binary predictors	Change from 0 (No) to 1 (Yes)
Categorical predictors	Each level relative to reference (No Service)

Table 4.3: Interpretation of model effects and predictor increments

Chapter 5

Results

This chapter presents the findings from the Bayesian spatial analysis of car-free households at the Small Area level in Ireland. The results are organised to reflect both the urban–rural divide and the main thematic groupings of variables. Section 5.1 summarises the overall urban–rural effect, highlighting the main differences in car-free household prevalence between these contexts. Section 5.2 reports in detail on the estimated effects for urban areas, presenting results by theme: (i) socio-demographic, (ii) socio-economic, (iii) built environment, and (iv) public transport and area attractiveness. Section 5.3 mirrors this structure for rural areas, providing thematic breakdowns for each group of variables. Section 5.4 presents the spatial and dispersion parameter estimates, quantifying residual spatial structure and model fit. Finally, Section 5.5 summarises the results of model validation and diagnostic checks.

Table 5.1: Bayesian spatial model fixed effects: main

Variable	Posterior Mean	SD	2.5% CrI	97.5% CrI
Intercept	-1.665	0.265	-2.185	-1.145
Rural (vs Urban)	0.228	0.619	-0.985	1.442
Sociodemographic Effects				
Prop. Age 20-34	1.855	0.062	1.733	1.976
Prop. Male	-0.407	0.104	-0.611	-0.202
Avg. Household Size (scaled)	-0.269	0.005	-0.278	-0.259
Prop. Lone Parent Families	0.923	0.046	0.834	1.013
Prop. Born Abroad	0.992	0.043	0.907	1.077
Prop. Recent Address Change	0.378	0.108	0.167	0.590
Prop. Volunteers	-0.635	0.109	-0.849	-0.421
Prop. Disabled	1.004	0.081	0.846	1.163
Prop. Carers	-0.391	0.193	-0.769	-0.013
Prop. Good Health	-1.138	0.254	-1.637	-0.640
Socioeconomic Effects				
Deprivation Index (scaled)	-0.258	0.006	-0.270	-0.245
Prop. No Central Heating	3.310	0.208	2.903	3.717
Prop. Managers/Professionals	-1.254	0.072	-1.394	-1.113
Prop. Agriculture	-1.154	0.252	-1.647	-0.661
Built Environment				
Prop. Apartment/Flat	0.080	0.020	0.041	0.119
Prop. Built 2016+	0.286	0.041	0.205	0.366
Prop. Renewable Energy	-0.358	0.043	-0.443	-0.273
Population Density (scaled)	0.043	0.004	0.035	0.051
Public Transport and Area Attractiveness				
PTAL: Low Level of Service	0.134	0.016	0.103	0.165
PTAL: Medium Level of Service	0.292	0.017	0.259	0.325
PTAL: Med-High Level of Service	0.565	0.018	0.529	0.601
PTAL: High Level of Service	0.675	0.024	0.627	0.723
Prop. Long Commute	-0.788	0.076	-0.938	-0.639
Log Food/Shopping Access (scaled)	0.005	0.004	-0.004	0.014
Log Social/Leisure Access (scaled)	0.013	0.005	0.003	0.023
Log Work Access (scaled)	0.024	0.006	0.013	0.036
Log Primary Education (binary)	-0.012	0.010	-0.032	0.007
Log Secondary Education (binary)	0.023	0.011	0.001	0.046
Log Tertiary Education (binary)	0.009	0.011	-0.013	0.030

Table 5.2: Bayesian spatial model fixed effects: interaction

Variable	**Posterior Mean**	**SD**	**2.5% CrI**	**97.5% CrI**
Interactions: Sociodemographics x Rural				
Deprivation Index (scaled) x Rural	0.063	0.018	0.027	0.099
Prop. Age 20-34 x Rural	-1.640	0.259	-2.148	-1.131
Prop. Male x Rural	0.285	0.296	-0.297	0.866
Prop. Born Abroad x Rural	-0.338	0.145	-0.622	-0.054
Prop. Recent Address Change x Rural	0.014	0.395	-0.762	0.790
Prop. Volunteers x Rural	0.531	0.218	0.103	0.959
Prop. Disabled x Rural	-0.118	0.211	-0.531	0.295
Prop. Carers x Rural	1.079	0.387	0.321	1.838
Prop. Good Health x Rural	-0.143	0.559	-1.239	0.954
Prop. Lone Parent Families x Rural	-0.151	0.171	-0.487	0.185
Prop. Managers/Professionals x Rural	-0.257	0.198	-0.646	0.132
Prop. Agriculture x Rural	1.012	0.283	0.458	1.566
Interactions: Socioeconomics x Rural				
Deprivation Index (scaled) x Rural	0.063	0.018	0.027	0.099
Prop. No Central Heating x Rural	-0.669	0.498	-1.646	0.307
Prop. Managers/Professionals x Rural	-0.257	0.198	-0.646	0.132
Prop. Agriculture x Rural	1.012	0.283	0.458	1.566
Interactions: Built Environment x Rural				
Avg. Household Size (scaled) x Rural	0.006	0.017	-0.027	0.040
Prop. Apartment/Flat x Rural	1.097	0.218	0.669	1.524
Prop. Built 2016+ x Rural	0.166	0.208	-0.241	0.573
Prop. Renewable Energy x Rural	-0.709	0.098	-0.901	-0.517
Population Density (scaled) x Rural	0.141	0.610	-1.056	1.338
Interactions: Transport and Area Attractiveness x Rural				
PTAL: Low Level of Service x Rural	-0.110	0.023	-0.155	-0.065
PTAL: Medium Level of Service x Rural	-0.245	0.075	-0.392	-0.098
PTAL: Med-High Level of Service x Rural	-0.799	0.337	-1.460	-0.139
PTAL: High Level of Service x Rural	0.000	1.000	-1.961	1.961
Prop. Long Commute x Rural	0.635	0.181	0.280	0.990
Log Food/Shopping Access (scaled) x Rural	0.031	0.012	0.008	0.054
Log Social/Leisure Access (scaled) x Rural	-0.034	0.013	-0.060	-0.008
Log Work Access (scaled) x Rural	-0.004	0.017	-0.037	0.030
Log Primary Education (binary) x Rural	0.027	0.023	-0.018	0.072
Log Secondary Education (binary) x Rural	0.028	0.026	-0.023	0.079
Log Tertiary Education (binary) x Rural	0.005	0.026	-0.047	0.057

5.1 Urban–Rural Effect

The model estimated a small, positive effect for rural areas compared to urban areas (estimate = 0.228, 95% Crl: -0.985 to 1.442), indicating that rural areas had a slightly higher predicted outcome. However, this difference was not supported by the model, as the 95% credible interval included zero, suggesting there is no strong evidence for a difference between rural and urban areas.

This finding is contrary to expectations, as rural areas are typically associated with lower rates of car-free households due to greater car dependency. The unexpected direction and lack of strong evidence may be partly explained by the much smaller rural sample size (approximately 4,000 rural vs. 14,000 urban observations), which reduces the precision of the estimate for rural areas. Additionally, the inclusion of other variables in the model, may account for much of the variation between rural and urban areas after adjustment.

5.2 Urban Effects

This section presents the estimated effects of the predictors on the prevalence of car-free households. Results are organised by thematic groupings: socio-demographics, socio-economics, housing and built form, and transport and Area Attractiveness. For each variable, the main effect is reported as its association with car-free households in urban areas (the reference group). Interaction effects indicate how these associations differ in rural areas. Where relevant, the combined effect for rural areas is also presented, calculated as the sum of the main effect and the corresponding interaction term. All results are shown as posterior means with 95% credible intervals. Variables whose credible intervals include zero are interpreted as having greater uncertainty regarding their association with the outcome. Results for main (urban) effects are shown in Table 5.1 and interactions effects are shown in Table 5.2, with detailed discussion below.

5.2.1 Socio-Demographic Effects (Urban)

All sociodemographic main effects included in the model demonstrated credible associations with the outcome in urban areas, as their 95% credible intervals did not include zero. IRR, percentage change, and CrIs for percentage change are displayed in table 5.3 below. Each effect is interpreted in terms of direction and strength.

Table 5.3: Sociodemographic effects (urban): percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	IRR	% Change	CrI Lower	CrI Upper
Prop. Age 20–34	1.855	1.204	20.38	18.93	21.85
Prop. Disabled	1.004	1.106	10.57	8.83	12.33
Prop. Born Abroad	0.992	1.104	10.43	9.50	11.37
Prop. Lone Parent Families	0.923	1.097	9.67	8.70	10.66
Prop. Address Change	0.378	1.039	3.86	1.69	6.08
Prop. Carers	-0.391	0.962	-3.84	-7.40	-0.13
Prop. Male	-0.407	0.960	-3.98	-5.93	-2.00
Prop. Volunteers	-0.635	0.938	-6.15	-8.14	-4.12
Prop. Good / Very Good Health	-1.138	0.892	-10.76	-15.10	-6.20
Avg. Household Size	-0.269	0.764	-23.55	-24.29	-22.80

Several sociodemographic variables demonstrated positive associations with the prevalence of car-free households. As these characteristics increased in an area, so did the likelihood of households being car-free. All positive effects discussed were statistically significant, with 95% credible intervals excluding zero, supporting evidence for their association with car-free households.

Proportion Aged 20-34

Areas with a higher proportion of young adults (aged 20-34) exhibited the strongest positive association with car-free household prevalence. Specifically, a 10 percentage point increase in this group is associated with a 20.4% (95% CrI: 18.9%, 21.9%) increase in car-free households. This finding suggests that younger adults are more likely to live without a car, potentially reflecting a combination of economic constraints, lifestyle preferences, or greater urban residency where alternative transport options are more readily available. This result is consistent with existing research which has identified younger age groups as less likely to own cars, particularly in urban contexts (see, e.g., Commins & Nolan, 2010; Liao & van Wee, 2023).

Proportion Disabled

The model also found a substantial positive effect for the proportion of disabled residents. A 10 percentage point increase in this group is associated with a 10.6% (95% CrI: 8.8%, 12.3%) increase in car-free households. This may be attributable to barriers to driving or car access among disabled populations, as well as a greater reliance on public or community transport solutions. The association aligns with previous studies highlighting reduced car ownership rates among people with disabilities (Liao & van Wee, 2023).

Proportion Born Abroad

Areas with a higher proportion of residents born outside Ireland showed a strong positive association with car-free households. Each 10 percentage point increase is associated with a 10.4% (95% CrI: 9.5%, 11.4%) increase in the prevalence of car-free households. This effect could reflect recent migrants' lower car ownership rates due to shorter residency, financial considerations, or greater tendency to live in urban, well-connected locations (Carroll et al., 2021).

Proportion Lone Parent Families

The prevalence of lone parent families was positively associated with car-free household rates, with a 10 percentage point increase linked to a 9.7% (95% CrI: 8.7%, 10.7%) rise in car-free households. This may be linked to constrained resources among lone parent households or residential concentration in areas with better public transport or urban amenities, echoing findings from other Irish studies (Eakins, 2013).

Proportion of Residents with a Recent Address Change

A higher proportion of individuals who had recently changed address also predicted a greater likelihood of car-free households. A 10 percentage point increase in this group is associated with a 3.9% (95% CrI: 1.7%, 6.1%) increase in the prevalence of car-free households. This relationship could reflect greater residential mobility among populations less dependent on car ownership, or a tendency for recently relocated residents to reside in more urban, accessible locations.
The following sociodemographic variables showed credible negative associations with the outcome in urban areas, as their 95% credible intervals are entirely below zero.

Proportion of Carers

A higher proportion of individuals providing unpaid care was associated with a lower prevalence of car-free households. Specifically, a 10 percentage point increase in carers is linked to a 3.8% decrease in car-free households (95% CrI: -7.4%, -0.1%). This may reflect greater transport needs among households with carers, potentially necessitating car access for mobility or support roles.

Proportion Male

Areas with a higher proportion of males exhibited a negative association with car-free household prevalence. A 10 percentage point increase in the male population is associated with a 4.0% decrease in car-free households (95% CrI: -5.9%, -2.0%). This may relate to gendered patterns in car access or employment-related travel.

Proportion Volunteers

A greater share of residents engaged in volunteering was linked to a lower prevalence of car-free households. Each 10 percentage point increase in volunteers corresponds to a 6.2% reduction in car-free households (95% CrI: -8.1%, -4.1%). This could be due to increased travel needs among volunteers or stronger ties to community activities requiring car use.

Proportion in Good or Very Good Health

Higher proportions of residents reporting good or very good health were associated with a 10.8% decrease in car-free households for every 10 percentage point increase (95% CrI: -15.1%, -6.2%). This may suggest that better health is correlated with higher car ownership, potentially due to increased mobility and activity levels.

Average Household Size

Areas with larger average household sizes showed the strongest negative association with car-free household prevalence in rural areas. A one standard deviation increase in average household size (SD = 0.42) is associated with a 23.6% decrease in car-free households (95% CrI: –24.3%, –22.8%). This likely reflects the increased need for car access in larger households, as well as potential associations with more suburban or family-oriented areas.

These findings indicate that, in urban areas, higher proportions of young adults (aged 20–34), residents with disabilities, residents born abroad, lone parent families, and individuals who recently changed address are all linked to a higher likelihood of households being car-free. Conversely, areas with larger households, more males, higher proportions of volunteers, better general health, and more carers are associated with a lower likelihood of households being car-free.

5.2.2 Socio-Economic Effects (Urban)

Table 5.4 presents the posterior means, incidence rate ratios (IRRs), and percent changes for each predictor, along with their 95% credible intervals, representing the expected change in car-free households for a one-unit increase in each variable (as defined by the increments).

Table 5.4: Socioeconomic effects (urban): percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	IRR	% Change	CrI Lower	CrI Upper
Prop. No Heating	3.310	1.392	39.24	33.69	45.03
Prop. in Agriculture	-1.154	0.891	-10.90	-15.19	-6.39
Prop. Managers/Professionals	-1.254	0.882	-11.78	-13.02	-10.53
Deprivation Index	-0.258	0.773	-22.71	-23.66	-21.76

Proportion with No Heating

Areas with a higher proportion of households without central heating showed the strongest positive association with car-free households in urban areas of the socio-economic predictors. A 10 percentage point increase in households without heating is associated with a 39.2% increase in car-free households (95% CrI: 33.7%, 45.0%). This likely reflects the influence of lower socioeconomic status on car ownership, as households without central heating likely have constrained resources limiting car access.

Proportion in Agriculture

A higher proportion of people employed in agriculture was associated with fewer car-free households. Each 10 percentage point increase is linked to a 10.9% decrease (95% CrI: -15.2%, -6.4%). This likely reflects the practical transport needs of the agricultural industry, where car use is essential due to spatial dispersion of work locations and limited public transport.

Proportion Managers/Professionals

Areas with a higher share of managers and professionals exhibited a negative association with car-free households. A 10 percentage point increase in this group is associated with an 11.8% decrease in car-free households (95% CrI: -13.0%, -10.5%). This may indicate higher car access among more affluent, professionally employed populations.

Deprivation Index

A one standard deviation increase in the Deprivation Index (SD = 10) was associated with a 22.7% decrease in car-free households in urban areas (95% CrI: –23.7%, –21.8%). This was the strongest negative effect found among socioeconomic predictors. This pattern indicates that higher incomes are linked with higher rates of car ownership in urban areas. This provides evidence to support the interpretation of the predictor "proportion with no central heating" as a related proxy for deprivation.
The results indicate that areas with a higher proportion of households without central heating had the largest positive association with car-free households, while higher deprivation, more managers/professionals, and greater employment in agriculture were negatively associated.

5.2.3 Built Environment Effects(Urban)

Table 5.5: Built Environment effects (urban): percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	IRR	% Change	CrI Lower	CrI Upper
Population Density	0.043	1.044	4.36	3.52	5.20
Prop. New Build (2016+)	0.286	1.029	2.90	2.07	3.73
Prop. Apartment/Flat	0.080	1.008	0.81	0.41	1.20
Prop. Uses Renewables	-0.358	0.965	-3.52	-4.34	-2.69

Population Density

Areas with higher population density were positively associated with car-free households. A one standard deviation increase in density (SD = 5,890 people per km^2) corresponds to a 4.4% increase in car-free households (95% CrI: 3.5%, 5.2%). This likely reflects that denser areas tend to have better public transport, walking infrastructure, and shorter distances to amenities, reducing reliance on cars.

Proportion New Build (2016+)

A higher proportion of recently constructed dwellings (2016 or later) was associated with a modest increase in car-free households. A 10 percentage point increase corresponds to a 2.9% increase in car-free households (95% CrI: 2.1%, 3.7%). Newer developments may be concentrated in areas with good transport access or smaller units, supporting lower car ownership.

Proportion Apartment/Flat

Areas with more apartments or flats showed a slight positive association with car-free households. A 10 percentage point increase is linked to a 0.8% increase in car-free households (95% CrI: 0.4%, 1.2%). This may reflect that multi-unit housing is typically more common in urban, transit-accessible locations.

Proportion Using Renewables

A higher proportion of households using renewable energy was associated with fewer car-free households. A 10 percentage point increase corresponds to a 3.5% decrease in car-free households (95% CrI: 2.7%, 4.3%). This could reflect socioeconomic or spatial patterns where renewable adoption correlates with larger, suburban homes that require car use.

5.2.4 Public Transport and Area Attractiveness (Urban)

Table 5.6: Public Transport and Area Attractiveness effects (urban): percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	IRR	% Change	CrI Lower	CrI Upper
PTAL: High Level of Service	0.675	1.963	96.33	87.14	105.97
PTAL: Med-High Level of Service	0.565	1.760	75.96	69.70	82.45
PTAL: Med Level of Service	0.292	1.339	33.90	29.57	38.39
PTAL: Low Level of Service	0.134	1.143	14.31	10.81	17.92
Work Attr.	0.024	1.025	2.46	1.31	3.63
Secondary Edu. Attr.	0.023	1.023	2.35	0.07	4.68
Social/Leisure Attr.	0.013	1.013	1.29	0.30	2.28
Tertiary Edu. Attr.	0.009	1.009	0.86	-1.26	3.03
Food Shopping Attr.	0.005	1.005	0.49	-0.39	1.38
Primary Edu. Attr.	-0.012	0.988	-1.24	-3.19	0.75

PTAL: High Level of Service

Areas with high public transport accessibility exhibited the largest positive association with car-free households. Compared to areas with no service, high-level PTAL areas are associated with a 96.3% increase in car-free households (95% CrI: 87.1%, 106.0%). This demonstrates that excellent public transport strongly supports car-free living.

PTAL: Med-High Level of Service

Areas with medium-high public transport accessibility are associated with a 76.0% increase in car-free households (95% CrI: 69.7%, 82.5%), highlighting the gradient effect of transport accessibility on car ownership decisions.

PTAL: Med Level of Service

Areas with medium public transport accessibility show a 33.9% increase in car-free households (95% CrI: 29.6%, 38.4%).

PTAL: Low Level of Service

Even areas with low public transport accessibility are associated with a 14.3% increase in car-free households (95% CrI: 10.8%, 17.9%) relative to no service, showing that any provision of public transport can support reduced car dependency.

Work Attractiveness

Greater attractiveness for workplaces is positively associated with car-free households, with a 2.5% increase per one standard deviation (95% CrI: 1.3%, 3.6%). Areas that are more attractive as employment locations may support lower car ownership by enabling more people to work locally or access jobs via sustainable modes.

Work Attractiveness

A one standard deviation increase in the log-transformed Work Attractiveness index (SD = 1.61) corresponds to multiplying the raw index by $\tilde{5}$. This change is associated with a 2.5% increase in car-free households (95% CrI: 1.3%, 3.6%). Areas that are more attractive as employment locations may support lower car ownership by enabling more people to work locally or access jobs via sustainable modes.

Secondary Education Attractiveness

The presence of at least one secondary education facility in an area is associated with a 2.4% increase in car-free households (95% CrI: 0.1%, 4.7%) compared to areas without such a facility. This modest positive association suggests that having a secondary school locally may support car-free living, potentially by making it easier for students and families to rely on local schools and sustainable transport options.

Social/Leisure Attractiveness

A one standard deviation increase in the log-transformed Social/Leisure Attractiveness index (SD = 0.41) corresponds to increasing the raw index by about 51%. This change is associated with a 1.3% increase in car-free households (95% CrI: 0.3%, 2.3%), indicating a very small but measurable effect on car-free households for areas that are attractive in terms of social and leisure amenities.

Tertiary Education Attractiveness

The model found no clear evidence that the presence of a tertiary education facility affects car-free household prevalence in urban areas (estimated effect: 0.9%; 95% CrI: –1.3%, 3.0%).

Food Shopping Attractiveness

The model found no clear evidence that greater attractiveness for food shopping has an effect on car-free household rates (estimated effect: 0.5%; 95% CrI: –0.4%, 1.4%).

Primary Education Attractiveness

The model found no clear evidence between the presence of a primary education facility and car-free household prevalence (estimated effect: –1.2%; 95% CrI: –3.2%, 0.8%).

5.3 Rural Effects Results

The results presented in this section reflect the combined effect of each predictor for rural areas. These effects are calculated by summing the main (urban) effect and the interaction effect for rural areas, providing the total estimated association between each variable and the prevalence of car-free households in rural settings. Percent changes and credible intervals are reported for a one-unit increase in each predictor (as defined in the increments), and represent the expected change in car-free household prevalence for rural small areas, holding other factors constant. This approach allows for a direct interpretation of how each factor operates in rural contexts, independent of the urban baseline. Predictors for which the credible interval does not include zero (indicating clear evidence of an association) are listed first and are ordered from the largest positive to the largest negative effect. Predictors where the credible interval includes zero, and thus the association is uncertain, are shown separately below the line.

5.3.1 Socio-Demographic Effects (Rural)

Table 5.7: Rural sociodemographic effects: percent change in car-free households for a one-unit increase in each predictor

Predictor	**Mean**	**IRR**	**% Change**	**CrI Lower**	**CrI Upper**
Prop. Disabled	0.887	1.093	9.27	4.85	13.88
Prop. Lone Parent Families	0.773	1.080	8.03	4.46	11.73
Prop. Born Abroad	0.654	1.068	6.76	3.77	9.83
Prop. Good / Very Good Health	-1.281	0.880	-12.02	-21.16	-1.83
Avg. Household Size	-0.262	0.769	-23.05	-25.58	-20.44
Prop. Carers	0.688	1.071	7.12	-0.70	15.56
Prop. Address Change	0.392	1.040	4.00	-3.76	12.39
Prop. Age 20–34	0.215	1.022	2.17	-2.89	7.50
Prop. Volunteers	-0.104	0.990	-1.03	-5.18	3.29
Prop. Male	-0.122	0.988	-1.21	-6.79	4.70

Proportion Disabled

A higher proportion of disabled residents in rural areas is associated with a 9.3% increase in car-free households for every 10 percentage point increase (95% CrI: 4.9%, 13.9%). This may reflect barriers to driving or greater reliance on public or community transport among disabled populations.

Proportion Lone Parent Families

A 10 percentage point increase in lone parent families in rural areas is linked to an 8.0% increase in car-free households (95% CrI: 4.5%, 11.7%). This may relate to limited financial resources.

Proportion Born Abroad

A higher proportion of residents born outside Ireland is linked to a 6.8% increase in rural car-free households per 10 percentage point increase (95% CrI: 3.8%, 9.8%). This could reflect recent migrants' lower car ownership rates or a tendency to live in more accessible locations.

Proportion Good / Very Good Health

A 10 percentage point increase in residents reporting good or very good health is associated with a 12.0% decrease in car-free households in rural areas (95% CrI: –21.2%, –1.8%). This suggests that better health is associated with higher rates of car ownership in rural settings.

Average Household Size

A one standard deviation increase in average household size (SD = 0.42) is associated with a 23.1% decrease in car-free households in rural areas (95% CrI: –25.6%, –20.4%). This represents the largest negative effect observed among the sociodemographic predictors for rural areas. Larger rural households are much less likely to be car-free, likely reflecting increased transport needs.

Proportion Carers

A 10 percentage point increase in carers in rural areas is associated with a 7.1% increase in car-free households (95% CrI: -0.7%, 15.6%). Because the credible interval includes zero, this effect is uncertain and the model did not find it to be credibly different from no effect.

Proportion Address Change

A 10 percentage point increase in residents who have recently changed address is associated with a 4.0% increase in car-free households in rural areas (95% CrI: -3.8%, 12.4%). As the credible interval includes zero, this effect should be interpreted with caution.

Proportion Aged 20–34

A 10 percentage point increase in young adults (aged 20-34) is associated with a 2.2% increase in car-free households in rural areas (95% CrI: -2.9%, 7.5%). The credible interval includes zero, indicating uncertainty in this effect.

Proportion Volunteers

A 10 percentage point increase in volunteering is associated with a 1.0% decrease in car-free households in rural areas (95% CrI: -5.2%, 3.3%). Because the credible interval includes zero, this association may not differ meaningfully from no effect.

Proportion Male

A higher proportion of males in rural areas is linked to a 1.2% decrease in car-free households for every 10 percentage point increase (95% CrI: -6.8%, 4.7%). The credible interval includes zero, indicating uncertainty in this estimate.

5.3.2 Socio-Economic Effects (Rural)

Table 5.8: Rural socioeconomic effects: percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	Increment	IRR	% Change	CrI Lower	CrI Upper
Prop. No Heating	2.641	per 10 pp	1.302	30.23	18.11	43.59
Prop. Managers/Prof.	-1.511	per 10 pp	0.860	-14.02	-17.30	-10.61
Deprivation Index	-0.194	per 1 SD	0.823	-17.66	-20.57	-14.64
Prop. Agriculture	-0.142	per 10 pp	0.986	-1.41	-6.72	4.21

Proportion with No Heating

A 10 percentage point increase in the proportion of households without central heating is associated with a 30.2% increase in car-free households in rural areas (95% CrI: 18.1%, 43.6%). This strong effect suggests that areas with poorer housing quality have much higher rates of car-free households, likely reflecting material deprivation and constrained car access.

Proportion Managers/Professionals

For every 10 percentage point increase in the proportion of those employed as managers and professionals, there is a 14.0% decrease in the prevalence of car-free households (95% CrI: –17.3%, –10.6%). This indicates that greater affluence and professional employment are linked to higher car ownership in rural settings.

Deprivation Index

A one standard deviation increase in the Deprivation Index (SD = 10.00) is associated with a 17.7% decrease in car-free households (95% CrI: –20.6%, –14.6%). This finding suggests that even in rural areas, car ownership rate are higher in areas that are more affluent.

Proportion in Agriculture

There is little evidence of an association between the proportion of agricultural employment and car-free household prevalence in rural areas (-1.4%; 95% CrI: –6.7%, 4.2%), as the credible interval includes zero. This contrasts with the finding for urban areas, where a meaningful negative association was observed. The lack of evidence in rural areas may reflect the smaller sample size, reduced statistical power, or greater homogeneity of agricultural employment in rural contexts, making it more difficult to detect a distinct effect after accounting for other socioeconomic factors.

5.3.3 Built Environment Effects (Rural)

Table 5.9: Rural built environment effects: percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	Increment	IRR	% Change	CrI Lower	CrI Upper
Prop. Apartment/Flat	1.177	per 10 pp	1.125	12.49	7.78	17.41
Prop. Built 2016+	0.452	per 10 pp	1.046	4.62	0.45	8.97
Prop. Renewables	-1.067	per 10 pp	0.899	-10.12	-11.83	-8.38
Pop. Density	0.183	per 1 SD	1.201	20.13	-63.71	297.61

Proportion Apartment/Flat

A 10 percentage point increase in the proportion of apartments or flats in a rural area is associated with a 12.5% increase in car-free households (95% CrI: 7.8%, 17.4%). This finding suggests that the presence of higher-density housing forms, even in rural settings, is linked to lower car ownership rates.

Proportion Built 2016+

Each 10 percentage point increase in the share of newly built dwellings (2016 or later) is linked to a 4.6% increase in car-free households (95% CrI: 0.5%, 9.0%), indicating a modest but positive association between recent construction and car-free living in rural areas.

Proportion Renewables

A 10 percentage point increase in the proportion of households using renewable energy is associated with a 10.1% decrease in car-free households (95% CrI: –11.8%, –8.4%). This suggests that renewable energy adoption is more common among rural households that own cars, possibly reflecting greater resources.

Population Density

There is little evidence of a meaningful association between population density (per 1 SD increase) and car-free household prevalence in rural areas (20.1%; 95% CrI: –63.7%, 297.6%), as the credible interval includes zero and the estimate is highly uncertain.

5.3.4 Public Transport and Area Attractiveness Effects (Rural)

Table 5.10: Rural public transport and area attractiveness effects: percent change in car-free households for a one-unit increase in each predictor

Predictor	Mean	Increment	IRR	% Change	CrI Lower	CrI Upper
Food Shopping Attr.	0.036	per 1 SD	1.037	3.66	1.33	6.04
Secondary Edu. Attr.	0.051	vs Not Attr.	1.052	5.24	0.00	10.75
PTAL: Low Service	0.024	vs No Service	1.024	2.41	-2.13	7.15
PTAL: Med Service	0.047	vs No Service	1.048	4.83	-9.48	21.39
PTAL: Med-High Service	-0.234	vs No Service	0.791	-20.87	-59.12	53.17
PTAL: High Service	0.675	vs No Service	1.963	96.33	-72.37	1295.04
Prop. Long Commute	-0.153	per 10 pp	0.985	-1.52	-4.96	2.04
Social/Leisure Attr.	-0.021	per 1 SD	0.979	-2.11	-4.63	0.48
Work Attr.	0.021	per 1 SD	1.021	2.10	-1.22	5.54
Primary Edu. Attr.	0.015	vs Not Attr.	1.015	1.48	-2.98	6.15
Tertiary Edu. Attr.	0.014	vs Not Attr.	1.014	1.39	-3.75	6.79

Food Shopping Attractiveness

A one standard deviation increase in area attractiveness in relation to food shopping is associated with a 3.7% increase in car-free households in rural areas (95% CrI: 1.3%, 6.0%). This positive effect suggests that access to better local shopping amenities may help support car-free living, even in less urbanised contexts.

Secondary Education Attractiveness

Rural areas with at least one secondary education facility have, on average, a 5.2% higher prevalence of car-free households compared to areas without such a facility (95% CrI: 0.0%, 10.8%). This suggests a modest positive association between the presence of a secondary school and car-free living in rural contexts, though the estimate is uncertain as the credible interval includes zero, indicating some uncertainty about the effect.

All other predictors

For all other public transport and area attractiveness predictors, the 95% credible intervals include zero. This indicates substantial uncertainty and no clear evidence for an association with car-free household rates in rural areas, after accounting for other modelled variables. The lack of a measurable effect for public transport accessibility is notable. Instead, other factors such as local amenities, household structure, and socio-economic context may be more important determinants of car-free living outside urban areas.

5.4 Spatial and Dispersion Parameter Estimates

This section presents the key hyperparameter estimates from the model. In addition to the fixed effects, the model estimates several parameters that capture residual variation and spatial dependence in the data. The estimates and 95% credible intervals for the size (overdispersion) parameter of the negative binomial distribution, the variance of the spatial random effect from the BYM2 component, and the mixing parameter phi, are summarised in Table 5.11, and their interpretation is discussed in detail.

Table 5.11: Model hyperparameter estimates

Parameter	Posterior Mean	SD	2.5% CrI	97.5% CrI
Size (negative binomial overdispersion)	14.795	1.145	12.566	17.066
Variance of spatial random effect	0.014		0.007	0.027
Phi (BYM2 mixing parameter)	0.568	0.163	0.256	0.867

Size (Negative Binomial Overdispersion)

The size parameter of the negative binomial distribution was estimated at 14.80 (95% CrI: 12.57, 17.07), indicating a moderate degree of overdispersion in the count of car-free households across small areas. In negative binomial regression, the size parameter determines the degree to which the variance exceeds the mean, following the relationship $\mathrm{Var}(Y) = \mu + \mu^2/\mathrm{size}$, where μ is the expected count. A larger size value indicates less overdispersion; as the size parameter increases, the negative binomial model approaches the Poisson model, which assumes the variance equals the mean. A a size parameter below 1 would indicate strong overdispersion (variance much greater than the mean), values between 1 and 5 reflect moderate overdispersion, and values above 10 suggest weak overdispersion. The estimated value of 14.80 implies that the data are somewhat more variable than under a Poisson model, however the degree of overdispersion is modest. The credible interval suggests reasonable certainty in this estimate. This supports the choice to use negative binomial distribution to capture the extra (relative to Poisson) variation in the outcome.

Variance of Spatial Random Effect

The variance of the spatial random effect, derived from the BYM2 spatial model, was estimated at 0.014 (95% CrI: 0.007, 0.027). This parameter quantifies the amount of unexplained spatial variation in the outcome after accounting for all included covariates. The relatively small value, with a credible interval that does not include zero, suggests that while most of the spatial variation is explained by the included covariates, there is still some residual spatial clustering present in the data. This means that unmeasured or unobserved local factors continue to play a small but non-negligible part in shaping the geographic pattern of car-free households. This result indicates that the model captures the majority of spatial variation in car-free household prevalence, with just a small amount of residual unexplained spatial structure.

Phi (BYM2 Mixing Parameter)

The BYM2 mixing parameter, (ϕ), was estimated at 0.57 (95% CrI: 0.26, 0.87). This parameter reflects the proportion of spatial variance attributable to structured (spatially correlated) effects as opposed to unstructured (random noise) variation. A value of phi close to 1 indicates predominantly structured spatial variation, while a value near 0 indicates mostly unstructured variation. The estimate of ϕ suggests that approximately 57% of the unexplained spatial variance in car-free households is due to structured spatial processes. This means that neighbouring small areas tend to be more similar than expected by chance. The remaining 43% of the variance is attributable to unstructured, spatially independent effects. The credible interval for ϕ does not include zero, indicating that structured spatial dependence is an important component of the unexplained variation in car-free households at the small area level in Ireland.

5.5 Model Validation and Diagnostics

Diagnostic Plots

Quantile–Quantile (QQ) Plot A quantile–quantile (QQ) plot is a graphical tool used to compare the distribution of model residuals to a theoretical distribution, such as the normal or, in this case, the negative binomial. If the model is appropriate, the points in the QQ plot should closely follow the 45-degree reference line, indicating that the residuals conform to the expected distribution. Deviations from this line suggest lack of fit, such as skewness or heavy tails not captured by the model.

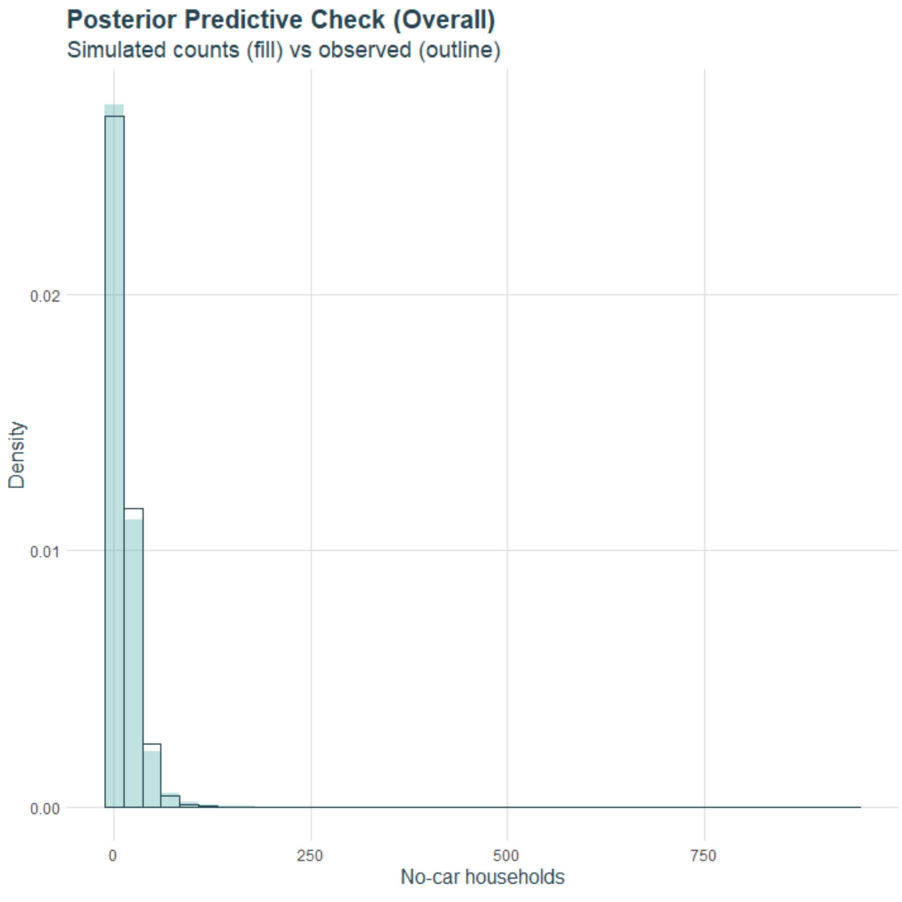

Figure 5.1: PPC Plot for Fitted Model

Posterior Predictive Check (PPC) Plot A posterior predictive check (PPC) plot is a Bayesian model diagnostic that assesses how well the fitted model can replicate the observed data. This is done by comparing the observed data to data simulated from the model's posterior predictive distribution. In this study, PPC plots were created by comparing the distribution of observed car-free household counts to those generated from the posterior predictive distribution of the final model. Good agreement between the observed and simulated data supports the adequacy of the model, while systematic differences may indicate model mis-specification or unmodelled features.

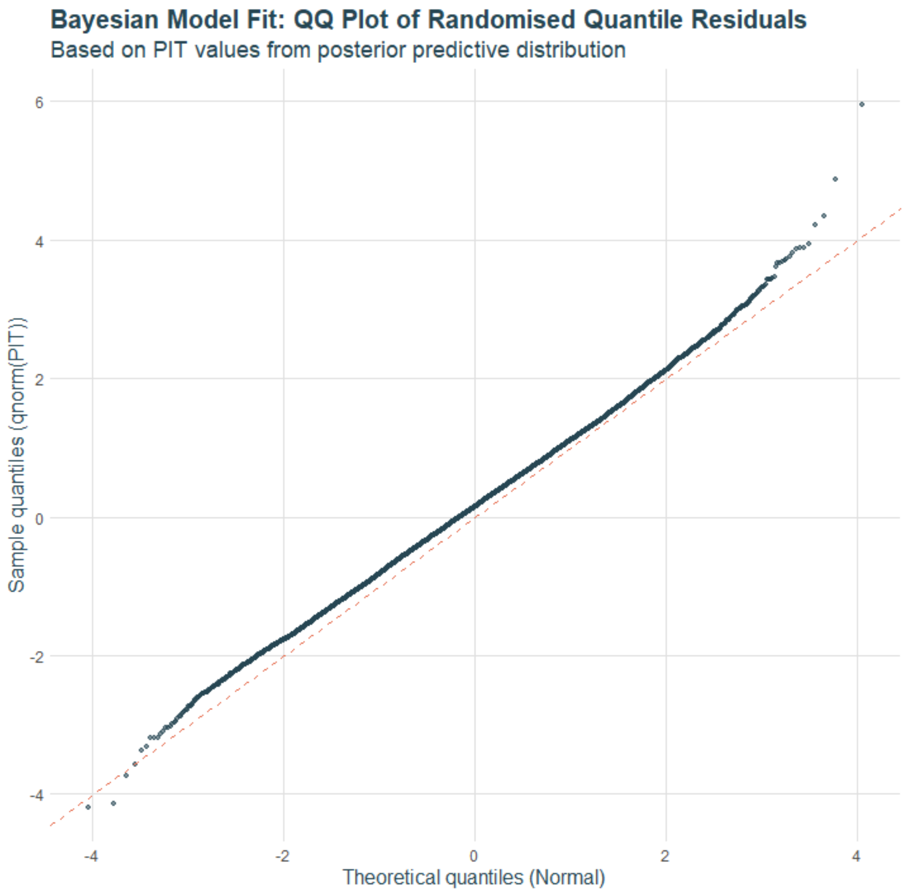

Figure 5.2: QQ Plot for Fitted Model

Chapter 6

Discussion

This chapter interprets and contextualises the main findings from the spatial analysis of car-free households in Ireland. Section 6.1 provides a concise summary of the principal results, highlighting key patterns and associations identified in the modelling. Section 6.2 situates these findings within the broader literature and policy landscape, offering an interpretation of their significance in the Irish context. Section 6.3 discusses the methodological strengths and limitations of the study. Finally, Section 6.4 presents suggestions for future research, identifying key avenues for extending and deepening the evidence base on car-free households.

6.1 Summary of Main Findings

Strongest Predictors in Urban Areas

In urban areas, the prevalence of car-free households is most strongly associated with:

- **Public Transport Accessibility:** The effect of public transport accessibility is by far the most pronounced, with areas enjoying the highest levels of service (PTAL: High) experiencing nearly a doubling (96% increase) in car-free households relative to areas with no service. Even modest improvements in service are associated with substantial increases in car-free living, highlighting the critical role of public transport provision.

- **Deprivation and Affluence:** A higher proportion of households without central heating is linked to a 39% increase in car-free households. Interpreted as a proxy for deprivation, this result indicates that material deprivation constrains car access. Similarly, the Deprivation Index is negatively associated with car-free households; a one standard deviation increase is linked to a 22.7% decrease in car-free households. Since higher values indicate greater affluence, this means that more affluent urban areas tend to have fewer car-free households. Both results are consistent with the expectation that car ownership increases with income and material resources.

- **Young Adult Population:** A higher share of young adults (aged 20-34) is associated with a 20% increase in car-free households, reflecting the tendency of this age group to live car-free, possibly due to economic factors or urban lifestyle preferences.

- **Disability:** Areas with higher proportions of people with disabilities show notable increases (about 10%) in car-free households, this could be due to access barriers to driving or resources.

Other strong negative associations in urban areas are observed for:

- **Average Household Size:** Larger average household size is with a 24% reduction in car-free households per SD (0.42) increase. This highlights the practical need for cars in larger households.
- **Professional Occupations:** Higher proportions of managers and professionals (−12% per 10 percentage points) and those employed in agriculture (−11% per 10 percentage points) are both associated with significantly fewer car-free households, reflecting both affluence and occupational necessity.

Other negative associations include a higher share of people reporting good health, a greater proportion of males, more volunteers, and more carers. These predictors were linked with lower car-free rates, potentially indicating mobility needs or lifestyle factors.

Strongest Predictors in Rural Areas

The pattern of effects in rural areas is notably different and in some cases counterintuitive:

- **Deprivation and Affluence:** A higher proportion of households without central heating is linked to a 30% increase in car-free households in rural areas. When interpreted as a proxy for material deprivation, this supports the finding that deprivation constrains car ownership, similar to the effect found for urban areas. The Deprivation Index is likewise negatively associated with car-free households, with a one standard deviation increase is linked to a 17.7% decrease in car-free households. Higher values reflect greater affluence, meaning that more affluent rural areas tend to have fewer car-free households. Both effects are consistent with the expectation that car ownership rises with income and improved living standards, even in rural settings.
- **Average Household Size:** In rural areas, average household size was the strongest negative predictor of car-free households. A one standard deviation increase in household size is associated with a 23.1% decrease in car-free household prevalence. This finding suggests that larger rural households are considerably more likely to own at least one car, likely reflecting greater transport needs among bigger families or multi-generational households.
- **Managers and Professionals:** Higher proportions of residents employed as managers or professionals are associated with significantly fewer car-free households in rural areas. Specifically, a 10 percentage point increase in this group predicts a 14.0% decrease in car-free household prevalence. This result reflects the link between higher socioeconomic status and increased car ownership, consistent with patterns observed in urban areas.
- **Built Environment:** The presence of apartments/flats, even in rural areas, is associated with a 12% increase in car-free households. This was the strongest positive built environment effect outside cities. Similarly, newer housing stock (built since 2016) shows a modest positive effect.
- **Sociodemographic Predictors:** Higher proportions of disabled residents (+9%), lone parent families (+8%), and residents born abroad (+7%) all predict more car-free households, with robust evidence.
- **Area Attractiveness:** Uniquely for rural contexts, greater food shopping attractiveness and the presence of a secondary school are both linked with higher car-free household prevalence, though these effects are smaller in magnitude than other effects found.

Key Urban–Rural Differences and Surprising Findings

Several predictors display substantially different effects in urban and rural areas.

- **Public Transport:** Unlike in urban areas, public transport accessibility does not show a clear association with car-free rates in rural areas after adjustment. This is a striking result, suggesting that other factors such as amenity proximity, household structure, and deprivation play a more decisive role in rural settings. This is a huge contrast to urban areas, where public transport is the dominant factor associated with car-free households.

- **Built Environment and Amenity Effects:** The influence of built environment features (apartments, new housing) and local amenities (food shopping, secondary schools) appears more pronounced in rural areas, supporting the idea that accessible local services can foster car-free living even in less urbanised settings.

- **Socio-Demographic Shifts:** Some predictors, such as the share of young adults, show a strong effect in urban areas but a much weaker or uncertain association in rural contexts. The positive association of disability and lone parenthood with car-free rates is robust in both contexts.

Other Notable Results

- **Renewable Energy:** The proportion of households using renewables is consistently associated with fewer car-free households in both urban and rural areas, possibly reflecting higher resource levels or larger, car-dependent homes.

- **Unexplained Spatial Variation:** The spatial random effect from the model is small but non-negligible, indicating that while most of the spatial patterning in car-free households is explained by observed variables, some local clustering remains.

- **Model Fit:** Model diagnostics, including QQ and posterior predictive plots, confirm a good overall fit and appropriate handling of overdispersion.

Overall Interpretation

Taken together, these results underline that while certain factors (public transport, deprivation, household structure) consistently shape car-free living, their relative importance differs meaningfully between urban and rural Ireland. Public transport is pivotal for supporting car-free living in urban contexts, while in rural areas, access to local amenities, built environment characteristics, and material deprivation take precedence. These findings have direct policy relevance for targeted interventions aimed at reducing car dependency and supporting sustainable mobility across diverse spatial contexts.

6.2 Interpretation in Context

The findings of this study substantially advance our understanding of the determinants and spatial distribution of car-free households in Ireland, confirming and extending patterns observed in previous international and Irish research. Several points of convergence and innovation are evident when results are viewed alongside the existing literature.

Convergence with Existing Literature

Consistent with the literature, this analysis demonstrates that car-free households are more prevalent among lower-income and deprived populations, single-person and non-family households, younger adults, and in higher-density or apartment-dominated areas (De Gruyter et al. 2025; Van Eenoo 2023; Commins and Nolan 2010; Caulfield 2011; McGoldrick and Caulfield 2015). The strong negative association of car-free living with household affluence, professional occupation, and household size aligns closely with findings from both Irish and international studies, confirming the central role of socio-economic and life stage factors.

In line with previous research, the built environment exerts a clear influence: apartment dwellers and residents of newer or denser housing are more likely to be car-free, while home ownership and single-family dwellings predict car ownership (Currans et al. 2023; Song and Wang 2017; Caulfield 2011). The results also corroborate the persistent urban–rural divide in car-free prevalence, with car-free living concentrated in cities and large towns, and much less common in rural areas (Carroll, Benevenuto, and Caulfield 2021; De Gruyter et al. 2025; Van Eenoo 2023; Laviolette et al. 2022).

A key finding echoing the literature is the critical importance of public transport accessibility for supporting car-free living in urban areas (Mulalic and Rouwendal 2020; Laviolette et al. 2022). As highlighted internationally, even modest improvements in urban transit access lead to substantial increases in the proportion of car-free households.

Novel Contributions and Extensions

This study also makes several distinct contributions. First, the explicit modelling of predictors at small area (SA) level using a spatially structured Bayesian negative binomial framework allows for more precise estimation of effects and better handling of spatial autocorrelation than most prior Irish studies, addressing one of the gaps identified in the literature.

Second, the inclusion of the multi-dimensional measure of "area attractiveness", in terms of food shopping, education, and other key amenities, represents a methodological innovation. The finding that food shopping and secondary education amenities are predictors of car-free prevalence in rural areas is not yet explored in the literature, and potentially demonstrates the possibilities for rural transport and planning policies that go beyond public transport provision.

Third, the finding that public transport accessibility is not a significant driver of car-free living in rural areas, after adjustment for other factors, provides new evidence for the limits of traditional rural transit solutions. Instead, local amenity access, deprivation, and household structure are the dominant predictors in these contexts, suggesting that targeted policies for rural Ireland should prioritise access to essential services and shared mobility over conventional transit expansion.

The analysis also uncovers some less-anticipated results, such as the positive association of disability and lone parenthood with car-free living in both urban and rural areas. This finding may reflect a complex interplay between transport disadvantage and support needs, and signals a need for further qualitative research and targeted policy responses.

Addressing The Research Questions

The five research questions will now be addressed below.

1. Which sociodemographic, housing, and built form factors are associated with the prevalence of car-free households in Ireland at the Small Area level?

The spatial model reveals that several sociodemographic and built environment factors are consistently associated with the prevalence of car-free households. In both urban and rural settings, material deprivation (proxied by the share of households without central heating) and lower affluence (as measured by the Deprivation Index) are linked to higher rates of car-free living. Average household size is a strong negative predictor: larger households are considerably less likely to be car-free, likely reflecting increased transport needs. Occupational status matters, with higher proportions of managers and professionals associated with lower car-free rates. In urban areas, a higher share of young adults (aged 20–34) and residents with disabilities both predict greater car-free prevalence, as does the presence of lone parent families and residents born abroad in both contexts. For housing and built form, apartment living (in both urban and rural areas) and newer housing stock are associated with higher car-free prevalence, while single-family dwellings and home ownership are linked to car ownership. These findings are consistent with international literature, but the fine spatial scale provides more precise evidence for the Irish context.

2. How does public transport availability and destination accessibility influence the likelihood of car-free households?

Public transport accessibility is the single most important predictor of car-free living in urban Ireland: high PTAL scores are associated with up to a 96% increase in car-free households. Even modest improvements in public transport access are associated with substantial increases in car-free prevalence in cities and large towns. However, in rural areas, public transport accessibility is not a significant predictor once other factors are taken into account, likely due to low service coverage and the necessity of car ownership in these contexts. In contrast, access to local amenities—such as food shopping and secondary education—plays a more important role in rural areas, albeit with effects smaller in magnitude than those seen for public transport in urban settings. The inclusion of a multi-dimensional "area attractiveness" index in this study represents a methodological advance, and findings confirm that proximity to destinations supports car-free living, particularly where public transport is limited.

3. What is the relationship between socio-economic deprivation and the prevalence of car-free households at the Small Area level?

Socio-economic deprivation remains a central factor in car-free prevalence. Both material deprivation (households without central heating) and lower Deprivation Index scores (less affluence) are associated with significantly higher rates of car-free households in both urban and rural areas. However, this association is not uniform: in deprived rural areas, being car-free is often involuntary and may be associated with transport poverty and social exclusion, while in urban areas, car-free living may also reflect voluntary lifestyle choices enabled by transport alternatives. The model confirms that income, employment status, and tenure status are key factors, and that car-free households are disproportionately concentrated in less affluent and more disadvantaged small areas.

4. How do the factors influencing car-free household prevalence differ between urban and rural areas?

The determinants of car-free living differ markedly by spatial context. In urban areas, public transport accessibility, young adult population, disability, and deprivation are the strongest positive predictors. In rural areas, deprivation and smaller household size are the dominant predictors, but built environment features (such as apartments) and local amenity access play a more prominent role than public transport. Occupational status (managers and professionals) is a consistent negative predictor across both settings, but agricultural employment reduces car-free rates only in urban areas (likely reflecting small urban–fringe settlements). Some predictors, such as the proportion of young adults, show strong effects in cities but are weaker or non-significant in rural areas. These differences highlight the importance of context-sensitive policy and analytic approaches.

5. What are the policy-relevant implications of any identified associations for sustainable transport planning in Ireland?

The findings have direct implications for sustainable transport and spatial planning. In urban areas, improving public transport access and service quality is the most effective lever for supporting car-free living. Policy interventions that enhance accessibility to jobs, shops, and services—particularly for younger adults and single-person households—can further reduce car dependency in cities. In contrast, rural areas require a fundamentally different policy approach. Here, the structural necessity of car ownership for many households means that transport policy should focus on targeted support for the most disadvantaged, improvements to local amenity provision, and the development of new forms of shared mobility or demand-responsive transport. The lack of effect for public transport accessibility in rural contexts highlights the need to move beyond conventional solutions and prioritise interventions that address local needs and service gaps.

Addressing the intersection of deprivation, transport poverty, and accessibility is essential for equitable planning in both urban and rural settings. The use of fine-grained spatial data and advanced statistical modelling in this study provides policymakers with actionable evidence to identify priority areas for intervention and to tailor strategies to local context. By delivering a holistic, spatially explicit analysis, this research underscores the importance of context-sensitive, evidence-based planning—ensuring that efforts to promote sustainable mobility also safeguard against exacerbating transport disadvantage for vulnerable populations.

6.3 Methodological Strengths and Limitations

Strengths

This study offers several notable strengths. First, by using the 2022 Census Small Area Population Statistics (SAPS), the analysis covers nearly 19,000 spatial units, allowing for detailed exploration of local variation in car-free household prevalence. This overcomes the limitations of previous Irish research that relied on aggregated data at county or regional level.

A further strength is the comprehensive, multi-source data integration. The analysis combines census data with the Pobal HP Deprivation Index, a novel Attractions Index, and the National Transport Authority's PTAL dataset. This combined approach enabled a comprehensive analysis of socio-demographic, economic, built environment, public transport and area attractiveness determinants.

The use of advanced spatial statistical methods is another key strength. Employing a Bayesian negative binomial spatial model (using INLA and the BYM2 specification) directly addresses overdispersion and spatial autocorrelation in the outcome variable. Including both structured and unstructured spatial random effects improves model fit and the reliability of parameter estimates, especially in areas with sparse data. The model was rigorously validated through residual and predictive checks (QQ plots, PPC plots), confirming adequate fit and proper handling of overdispersion. The BYM2 spatial specification captured most, but not all, of the residual clustering in car-free household rates.

By explicitly accounting for spatial variation, urban–rural heterogeneity, and a broad set of structural and contextual predictors, this study addresses several of the main gaps identified in the literature review:

- It applies advanced spatial modelling techniques at a fine geographic scale, providing new evidence on the context-specific drivers of car-free living in Ireland;
- It incorporates a detailed measure of area attractiveness, a factor largely absent from previous research, especially in Irish and rural contexts;
- It demonstrates that the policy levers for reducing car dependency differ markedly between urban and rural settings; public transport investment in cities versus local amenity and service provision in rural areas.

Additionally, the study explicitly models urban–rural heterogeneity through interaction terms. This approach uncovers context-specific effects and avoids masking meaningful differences between settlement types, addressing a key gap identified in the literature. The methodological framework is transparent and replicable, offering clear guidance for policymakers and researchers interested in spatial patterns of car-free living, deprivation, and accessibility in Ireland.

Limitations

Despite its strengths, the study also faces several limitations. While the dataset includes all Irish small areas, the rural sample represents only about 22% of the total (approximately 5,000 out of 18,894 SAs). This imbalance reduces statistical power for detecting rural-specific effects, contributing to large credible intervals and greater uncertainty in rural parameter estimates.

Some predictors indices displayed extreme right-skew and sparsity, with many areas reporting zero access. While the education variables were recoded as binary to address this, area attractiveness in terms of food shopping others remained continuous, which may have affected robustness and interpretability. Future work should consider systematically recoding such sparse variables to better capture their effects and enhance comparability.

A particular challenge arises in the interpretation of population density effects. The standard deviation for population density is extremely large (SD $\approx$ 5,890 people/km^2), reflecting a highly skewed distribution driven by a handful of extremely dense urban cores (mainly in Dublin). As a result, a one-standard-deviation increase represents a dramatic and often unrealistic change for most areas. The effect size for population density should therefore be interpreted with caution, as it is disproportionately influenced by a small subset of very dense SAs, and may not reflect typical shifts in density experienced elsewhere in Ireland.

As with most census-based spatial studies, the cross-sectional design precludes any inference about causality or changes over time. The study cannot distinguish between car-free status by choice or constraint, or capture temporal shifts in response to economic shocks or policy changes. Although the model incorporates a broad array of predictors, some potentially relevant factors, such as cultural attitudes, historical land use, or micro-level transport interventions—remain unmeasured due to data limitations. The residual spatial random effect in the model suggests that some unexplained geographic clustering persists.

Summary

Overall, this study demonstrates the value of integrating high-resolution spatial data with advanced statistical techniques, while also highlighting the persistent challenges of research, including sample size imbalances, variable skew, and interpretation of effects for highly non-normal predictors such as population density. These strengths and limitations should guide both the interpretation of findings and future work in this area.

6.4 Suggestions for Future Research

While this study makes important advances in understanding the spatial and socio-economic drivers of car-free households in Ireland, several avenues remain open for future investigation:

1. **Longitudinal Analysis:** The present research uses cross-sectional data from the 2022 Census. Future studies could employ longitudinal or panel data, when available, to track how car-free household prevalence and its determinants change over time—particularly in response to policy interventions, economic shifts, or transport network improvements.

2. **Qualitative and Mixed Methods:** Further qualitative research could help distinguish between households that are car-free by choice versus by constraint. Interviews or surveys could provide richer insights into the lived experiences, motivations, and challenges faced by different groups, complementing the quantitative findings.

3. **Micro-Level and Behavioural Data:** Integrating micro-level behavioural datasets—such as individual travel diaries, GPS mobility data, or survey-based attitudinal measures—could provide a more granular understanding of mobility choices, particularly in relation to active modes, shared mobility, and telecommuting.

4. **Policy Evaluation:** Future work could explicitly evaluate the impact of specific policy interventions, such as new bus routes, mobility hubs, or rural shared mobility pilots, using quasi-experimental or difference-in-differences methods to assess causal effects on car-free living.

5. **Broader Accessibility Metrics:** While this study introduces a comprehensive area attractiveness index, further research could expand on this by developing multidimensional accessibility and opportunity metrics that account for digital access, health services, or childcare.

6. **International Comparative Studies:** Comparative research across countries or regions using harmonised spatial and statistical methods would help contextualise Ireland's patterns in a broader European or global perspective.

7. **Modelling Innovation:** Methodological advances—such as dynamic Bayesian spatial models, machine learning approaches for spatial prediction, or simulation-based policy modelling—could further refine our understanding of spatial heterogeneity and policy levers.

By pursuing these directions, future research can deepen understanding of both the drivers and consequences of car-free living, strengthen the evidence base for policy, and help ensure that sustainable mobility transitions are equitable, effective, and context-sensitive.

Chapter 7

Conclusion

This dissertation provides the first spatially explicit, small-area analysis of car-free households in Ireland using a Bayesian negative binomial modelling framework. Drawing on integrated census, deprivation, accessibility, and amenity datasets, the study identifies distinct urban–rural patterns and highlights the central roles of public transport, deprivation, household structure, and local amenities in shaping car-free living.

The results demonstrate that, in urban areas, improved public transport and high residential density are the strongest enablers of car-free households, while deprivation and smaller household size are key drivers in rural settings. The absence of a strong public transport effect in rural areas underscores the need for tailored policies focused on local services and alternative mobility options. The innovative inclusion of a multi-domain area attractiveness index adds new empirical evidence to the literature, particularly regarding the importance of local amenities in supporting car-free living outside cities.

Methodologically, the study advances the field through its application of advanced spatial Bayesian techniques at an unprecedented spatial resolution for Ireland, providing robust, policy-relevant insights for the design of targeted, equitable interventions.

In summary, this work makes a substantive contribution to both academic understanding and practical policy on sustainable mobility. By identifying the spatial and social contours of car-free living, the dissertation offers actionable evidence to inform the ongoing transition toward more inclusive, low-carbon transport systems in Ireland. Continued research—integrating longitudinal, behavioural, and policy evaluation approaches—will be vital to ensuring that future mobility transitions are both sustainable and socially just.

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Appendix A

Supplementary Tables

Sociodemographic Effects
prop_age20_34
prop_male_T1
prop_bp_abroad
prop_addr_change
prop_singles
prop_lone_parent_families
prop_volunteers
prop_disabled
prop_carers
prop_good_health
avg_household_size
avg_family_size
prop_one_person_hh
prop_couple_with_children
prop_multi_family_units

Socioeconomic Effects
dep_index
prop_managers_prof
prop_agriculture
prop_unemployed
prop_no_or_primary

Built Environment
prop_apt_flat
prop_built_2016plus
prop_homeowners
prop_no_heating
prop_has_renewables
pop_density

Public Transport and Attraction Indices
PTAL_level
work
employer_business
food_shopping
social_leisure
friends_family
primary_edu
secondary_edu
tertiary_edu
prop_long_commute
prop_work_from_home

Spatial Context
urban_rural

Table A.1: List of variables before variable selection