Understanding the impact of the COVID-19 pandemic using Bayesian modelling and spatial statistics

A dissertation submitted for the degree of
Doctor of Philosophy

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Abstract

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, has reshaped public health, societal behaviors, and governance on an unprecedented scale. Its rapid global spread, coupled with its profound health and social impacts, necessitated swift and diverse responses, ranging from non-pharmaceutical interventions like lockdowns to large-scale vaccination campaigns. This thesis investigates three interconnected aspects of the pandemic, each offering critical insights into its health, societal, and policy impacts, while addressing key knowledge gaps that have implications for managing future global health crises.

The first part of this research focuses on **evaluating the effectiveness of pandemic mitigation strategies in Ireland**, a country characterized by its distinct county-based public health system. By developing and applying a Bayesian Hierarchical Poisson Regression model, this study examines the impact of lockdown measures and vaccination rates on overall mortality. The results highlight that stringent public health interventions, implemented at varying levels across counties, were instrumental in reducing COVID-19-related deaths. The analysis also quantifies the number of lives saved by these measures, offering robust evidence for the importance of timely and localized responses to public health emergencies. These findings not only provide actionable insights for optimizing Ireland's public health framework but also offer lessons for other nations in refining their pandemic preparedness and response strategies.

The second part of the thesis investigates **the long-term health consequences of the pandemic, with a focus on its impact on cardiovascular disease (CVD)**. Using data from 26 European countries and a Bayesian Hierarchical Logistic Regression model, the study reveals a 20% increase in the risk of CVD following COVID-19 infection, particularly among older adults and individuals with pre-existing conditions such as hypertension, diabetes, chronic lung disease, and obesity. These findings underscore the need for integrated public health strategies that address both infectious diseases and non-communicable diseases during and beyond pandemics. The analysis also highlights regional disparities in the pandemic's cardiovascular impacts, emphasizing the importance of tailored interventions to mitigate the long-term health burdens exacerbated by COVID-19.

The third component examines **how the pandemic disrupted societal norms**

and influenced crime trends with an analysis of this for crimes in England and Wales. Leveraging spatiotemporal Bayesian modeling and crime data from local authorities, the study investigates the relationship between lockdown measures and shifts in crime patterns. The findings reveal significant decreases in residential burglary and vehicle theft during lockdown periods, while crimes such as anti-social behavior and drug-related offenses increased, driven by heightened social tensions and altered community dynamics. This work provides a comprehensive understanding of how public health measures influenced criminal behavior and offers practical recommendations for integrating crime prevention strategies into pandemic responses.

Collectively, **this thesis provides a multidimensional exploration of the COVID-19 pandemic's impact, combining advanced statistical modeling with spatiotemporal analyses to offer novel insights into its health, societal, and policy dimensions**. By addressing the effectiveness of mitigation strategies, the long-term health impacts, and the societal disruptions caused by the pandemic, this research contributes to the broader understanding of pandemic management. It offers evidence-based recommendations to inform future public health strategies, ensuring better preparedness and resilience for global health crises to come. Overall, **our work demonstrates that advanced statistical models and spatial statistics are a robust set of tools for application to real-world problems. The work presented here in this thesis provides a strong argument for their application to other types of problems with an inherently statistical characteristics**.

Declaration

I, Niloufar Pourshir Sefidi, hereby declare that I have produced this manuscript myself, without the prohibited assistance of third parties and have only used the resources that were explicitly allowed.

This work was conducted from September 2021 to August 2025 under the supervision of Dr. Peter Mooney in the Hamilton Institute, Maynooth University.

Niloufar Pourshir Sefidi,
Maynooth, Ireland,
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Collaborations

Peter Mooney: As my supervisor, Dr. Mooney provided supervision and collaboration on the work presented in all chapters, including thorough review and managing the editing of each chapter.

Amin Shoari Nejad: Dr. Shoari Nejad, contributed to the work in Chapters 3 and 5, by reviewing and editing the manuscript.

Publications

Some of the work in this thesis, has been published in peer-reviewed journals or conference proceedings, or presented at conferences.

Peer-reviewed conference articles:

- Pourshir Sefidi, N., Mooney, P., Exploring the effects of socioeconomic factors on voter preferences: A case-study of France 2022. *31st Geographical Information Science Research UK (GISRUK) Conference*, (2023).
`https://doi.org/10.5281/zenodo.7823388`
- Pourshir Sefidi, N., Shoari Nejad, A., Mooney, P., An investigation of the effects of lockdowns and COVID-19 vaccinations in Ireland. *26th AGILE Conference on Geographic Information Science "Spatial data for design", Delft, The Netherlands*, AGILE: GIScience Series 4 (2023): 37.
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Peer-reviewed journal articles:

- Pourshir Sefidi, N., Mooney, P., An exploration of the connection between COVID-19 and cardiovascular disease (CVD) in European countries. *Journal of Public Health*, pp.1-11, (2024). `https://doi.org/10.1007/s10389-024-02372-2`
- Pourshir Sefidi, N., Shoari Nejad, A., Mooney, P., Effects of Pandemic Response Measures on Crime Counts in English and Welsh Local Authorities. *Journal of Applied Spatial Analysis and Policy*, 18(1), p.15, (2025).
`https://doi.org/10.1007/s12061-024-09614-6`

Reproducibility Statement

This thesis follows the principles of reproducible research. The data and code necessary to replicate the results and analyses presented in this work are publicly available in dedicated GitHub repositories, organized by chapter. Each repository includes detailed documentation, such as a `README.md` file, which outlines the repository's structure and provides step-by-step instructions for reproducing the results. The repositories are as follows:

- Chapter 3 assesses the impact of lockdowns and COVID-19 vaccinations on mortality in Ireland using a Bayesian Hierarchical Poisson Regression model. Reproducible code and data are available at:
  `https://github.com/nilips70/Covid-Project`
- Chapter 4 explores the connection between COVID-19 and cardiovascular disease in European countries using Bayesian hierarchical logistic regression models. The code and data required to reproduce the results are available at:
  `https://github.com/nilips70/COVID19-and-CVD`
- Chapter 5 examines the effects of pandemic response measures on crime counts across local authorities in England and Wales using Bayesian spatio-temporal modeling. Reproducible code and data are available at:
  `https://github.com/nilips70/Crime-Modelling`
- Appendix A investigates the effects of socioeconomic factors on voter preferences in the 2022 French presidential election using Poisson log-linear spatial models. Reproducible code and data are available at:
  `https://github.com/nilips70/French-Election-2022`

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1 Introduction

1.1 Motivation

In late December 2019, the COVID-19 outbreak, caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), first emerged in Wuhan, China, and swiftly spread across the globe [249]. As the virus continued its rapid spread, the World Health Organization (WHO) declared COVID-19 a pandemic in March 2020 [294]. COVID-19 is a respiratory disease [133], transmitted through close contact with infected individuals via secretions such as saliva or respiratory droplets, or indirectly through contact with contaminated surfaces [133]. Common symptoms include fever, fatigue, and dry cough [267], which typically appear following an incubation period of 1 to 14 days, with an average onset around five days [133, 303]. People of all ages can contract COVID-19, but the risk of severe illness progressively increases with age, starting from around 60 years old [299]. Most young individuals and children (81%) experience mild symptoms or remain asymptomatic [303]. When symptoms do occur, they are typically limited to mild pneumonia, allowing recovery without specific treatment. However, older individuals and those with underlying medical conditions such as diabetes, hypertension, lung or heart disease, immune disorders, and obesity are at a significantly higher risk of developing severe respiratory complications [311, 52]. These complications may require hospitalization, intensive care, or, in some cases, can result in death [59, 248].

As of February 2025, COVID-19 continues to spread globally, with new cases and fatalities still being reported [293, 197, 176]. According to the WHO, approximately 777 million COVID-19 cases have been recorded worldwide, resulting in around 7 million deaths to date [293]; however, there are substantial differences between countries in the number of reported incidences. Figure 1.1 and Figure 1.2 show the cumulative number of confirmed COVID-19 cases per 100,000 population and cumulative number of confirmed COVID-19 deaths per 100,000 population as of February 16, 2025, respectively [176].

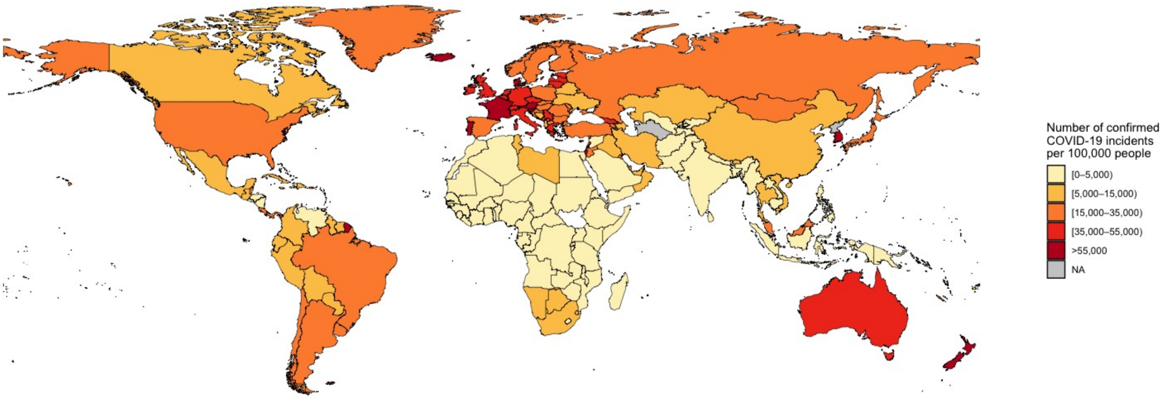


Figure 1.1: Cumulative numbers of confirmed COVID-19 cases per 100,000 people, 16 February 2025.

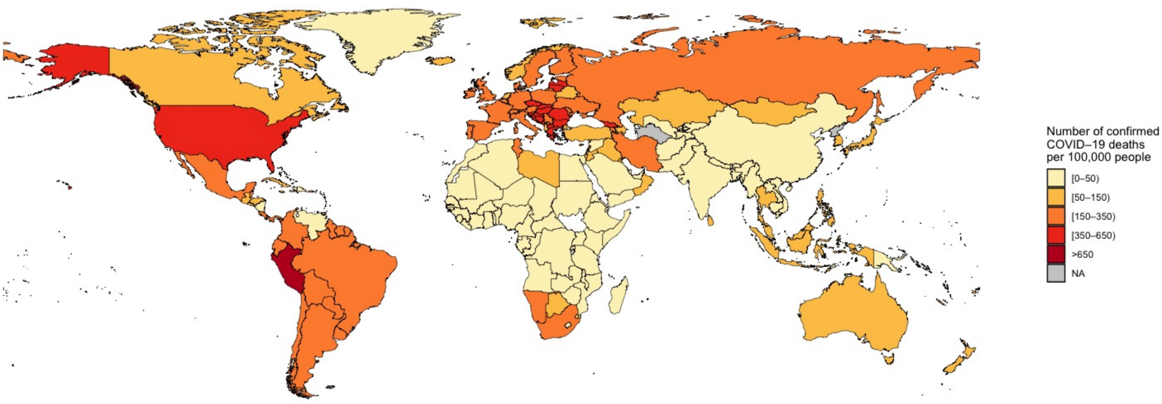


Figure 1.2: Cumulative numbers of confirmed COVID-19 deaths per 100,000 people, 16 February 2025.

COVID-19 is transmitted through both direct and indirect contact with infected individuals. As a result, its transmission has been closely linked to individual behaviours, such as wearing face masks, regularly cleaning and disinfecting hands and frequently touched surfaces and maintaining physical distance from others [198]. Although individual behaviours were vital in curbing the spread of COVID-19, they were not sufficient on their own. Many people struggled to fully adapt because public transportation was still widely used for commuting, schools and offices remained open, and pubs and restaurants continued to facilitate close-contact interactions. Hence, government action was also necessary to limit the spread. In the early stages of the pandemic, before vaccines and antiviral treatments were available, most governments worldwide relied on non-pharmaceutical interventions to curb the virus's spread. These measures included social distancing mandates, school and workplace closures, restrictions on travel and large gatherings and localized or nationwide lockdowns. While critical in slowing the virus's initial spread [13, 207], these interventions varied widely in design and enforcement due to differences in healthcare infrastructure, governmental resources, public compliance, and the severity of outbreaks in each region. Countries such as China, Ireland, the UK, and Spain implemented nationwide lockdowns, whereas Norway, Finland, and Canada opted for partial lockdowns [22].

The development and rollout of vaccines marked a turning point in the fight against COVID-19. By late 2020, several vaccines, including those from Pfizer-BioNTech, Moderna, AstraZeneca received emergency use authorization [96], initiating a global vaccination campaign. Governments initially prioritized high-risk groups, such as healthcare workers, the elderly, and individuals with underlying health conditions [296]. As vaccine production scaled up, programs expanded to broader populations, significantly reducing severe illness, hospitalizations, and deaths [188, 66].

Despite these advancements, COVID-19 continues to persist globally [298, 89, 176], though with reduced severity compared to the height of the pandemic. One of the key challenges has been understanding the extent to which government interventions, such as lockdowns and vaccination programmes, were effective in reducing fatalities and mitigating the worst outcomes during the crisis [283, 188, 196]. As the immediate threat subsided, attention increasingly shifted from short-term containment to the broader and more complex questions of COVID-19's lasting effects on public health and society. Beyond the acute respiratory complications seen early in the pandemic, many individuals went on to experience prolonged symptoms or developed new health issues, including cardiovascular, diabetes, and neurological conditions, well after their initial recovery [6, 304, 134]. These persistent or evolving health risks highlight the lingering effects of the virus and underscore the multifaceted challenges of managing its aftermath.

In addition to these direct health burdens, the pandemic created wide-ranging disruptions that reshaped social and economic life on a global scale. Public health measures, such as lockdowns and social distancing, curtailed freedom of movement and triggered sudden changes in employment, schooling, and social interaction [22, 154]. While effective at slowing transmission, such measures had adverse economic and mental consequences, especially for vulnerable populations already struggling with financial or social inequalities [123, 185, 74]. These social and economic upheavals also had unintended consequences for public safety and patterns of criminal activity. At the same time, certain types of crime declined as people stayed home such as burglary and shoplifting, whereas domestic incidents and cybercrime rose in frequency [130, 270]. Collectively, these issues underscore the pandemic's profound societal footprint and illustrate the deep interconnections between public health and community well-being.

Therefore, significant gaps persist in understanding the virus's short- and long-term effects on both health and societal systems, particularly regarding how these impacts vary across different regions and populations, underscoring the need for continued research and monitoring.

1.2 Bridging Knowledge Gaps: Focus Areas of This Thesis

Addressing the critical knowledge gaps highlighted by the COVID-19 pandemic is essential for understanding its multifaceted health and societal impacts. This thesis contributes to this effort by focusing on three key areas of investigation, each examining a distinct yet interconnected aspect of the pandemic. By leveraging advanced statistical models and spatiotemporal data analysis, this research provides a comprehensive perspective on the pandemic's effects, offering insights that are crucial not only for addressing its ongoing challenges but also for informing future public health responses and crisis preparedness.

To ensure a structured and in-depth analysis, the chapters in this thesis are organized based on the duration of the datasets analyzed, allowing for a detailed examination of each phenomenon over its respective time span while collectively offering a broad understanding of COVID-19's impacts across different domains. As a result, Chapter 3, which analyzes pandemic mitigation strategies, uses data spanning from January 2020 to August 2022, making it the shortest dataset in the thesis. Chapter 4, which investigates the long-term health consequences of COVID-19, covers a longer period from October 2019 to September 2021 to capture pre-pandemic and pandemic effects. Finally, Chapter 5 examines crime trends over the longest time-span from January 2015 to May 2023, allowing for a comprehensive assessment of patterns before, during, and after the pandemic.

1.2.1 The Effectiveness of Pandemic Mitigation Strategies

The COVID-19 pandemic posed unprecedented challenges to public health systems worldwide, requiring swift implementation of mitigation strategies to reduce mortality and curb virus transmission. Health systems, already under strain in many regions, faced an acute shortage of resources, including medical personnel, hospital beds, and essential supplies like ventilators and personal protective equipment [214, 23, 35, 236]. Early interventions, such as lockdowns and other non-pharmaceutical measures like mask mandates and hygiene promotions, sought to protect populations while buying time for the development of effective treatments, such as antiviral medicines and vaccines. These measures were often accompanied by public awareness campaigns to ensure compliance and address misinformation. Cultural differences [178], public trust in government mitigation efforts [74], vaccine hesitancy [100], and access to resources played critical roles in shaping the outcomes of these strategies. Furthermore, the application of these measures at varying levels of strictness across different regions and over time resulted in diverse outcomes.

However, the effectiveness of these interventions remains a subject of debate, as evidence indicates significant variation in their outcomes. While some studies highlight the life-saving potential of such interventions [196, 302], others question their effectiveness [128, 57, 167], pointing to inconsistencies in outcomes. These disparities highlight the need for comprehensive analyses that account for region-specific factors and temporal variations influencing public health outcomes. Ireland presents a compelling case study for evaluating the impact of these strategies due to its distinct county-based public health approach, which combines centralized coordination with regional implementation. However, variability in healthcare capacity, population density, and adherence to public health measures across counties may have contributed to differences in the effectiveness of these interventions. To address these spatial disparities, our research conducts a county-level analysis, enabling a more granular assessment of the impact of lockdowns and vaccination efforts across different regions in Ireland. By examining the effectiveness of pandemic mitigation strategies within this framework, our research addresses a critical gap in the existing literature, shedding light on how tailored measures may improve outcomes in a specific national context. Furthermore, such an analysis not only provides evidence for assessing the extent to which these interventions reduced mortality but also offers practical insights for optimizing public health responses in future crises.

In Chapter 3, we describe our work on evaluating the impact of pandemic mitigation strategies on mortality count in Ireland. This involves scraping data, compiling and integrating diverse datasets, conducting data quality checks, and implementing a Bayesian hierarchical Poisson regression model to account for both spatial and temporal variations and ultimately quantifying the number of lives saved during the COVID-19 pandemic.

1.2.2 Long-Term Health Consequences: COVID-19 and Cardiovascular Disease

Cardiovascular disease (CVD) remains the leading cause of mortality globally and across Europe, placing a considerable burden on healthcare systems and public health resources [79, 301]. The onset and progression of CVD are strongly linked to well-documented risk factors, including hypertension [99], diabetes [161], obesity [5], and chronic respiratory conditions [48]. These comorbidities are particularly prevalent among older adults, further elevating their susceptibility to cardiovascular complications [78].

The COVID-19 pandemic introduced an additional layer of complexity to this existing burden. COVID-19 infection has been shown to trigger systemic inflammation, coagulation abnormalities, and myocardial injury, which can exacerbate pre-existing cardiovascular conditions or lead to new-onset CVD [278, 232, 75]. Individuals with underlying risk factors, such as hypertension, diabetes, and obesity, faced significantly heightened risks of severe outcomes and mortality during the pandemic [77]. Moreover, emerging evidence indicates that even after recovering from acute infection, COVID-19 survivors remain at an elevated risk of cardiovascular complications [231, 304]. This highlights the pandemic's enduring impact on long-term cardiovascular health and its contribution to the existing burden of CVD. Understanding this interplay between COVID-19 and CVD is critical for identifying the broader health implications of the pandemic, particularly within vulnerable populations. A detailed investigation into how these effects vary spatially across Europe is essential for informing effective public health strategies and addressing the ongoing burden of CVD in the post-pandemic era. To address this gap, our research examines the influence of COVID-19 on the burden of CVD in Europe, particularly among older adults. The pandemic's strain on healthcare systems, compounded by pre-existing risk factors, underscores the timeliness of this investigation. By exploring regional disparities and identifying factors that amplify cardiovascular risks, this study aims to provide actionable insights for managing the dual burden of infectious and non-communicable diseases during and beyond health crises.

Chapter 4, describes our work on analyzing the association between COVID-19 and CVD across 26 European countries. This includes integrating datasets, applying Bayesian hierarchical model to assess regional variations, and interpreting the results within the broader context of public health. Our findings highlight how the pandemic has affected cardiovascular health, showing the important role of risk factors like obesity, hypertension, and diabetes. This insight provides valuable evidence to help shape targeted interventions and inform policy decisions.

1.2.3 Crime Trends During the COVID-19 Pandemic

The COVID-19 pandemic disrupted societal routines and mobility patterns on an unprecedented scale, leading to significant changes in crime trends [185, 130]. Government-imposed measures, such as lockdowns, travel restrictions, and the closure of non-essential businesses, fundamentally altered the opportunities and environments for criminal activity [270]. For instance, with more people staying at home during lockdowns, residential burglaries declined [276], while reductions in vehicular traffic led to fewer instances of vehicle theft [14]. Conversely, crimes such as anti-social behaviour and drug-related offences surged [123, 254], driven by heightened social tensions, economic pressures, and changes in community dynamics. These shifts highlight how government-imposed restriction measures, though essential for controlling the pandemic, created unanticipated changes in crime patterns. Moreover, the gradual lifting of restrictions and the official end of pandemic introduced new challenges, as crime rates for some offences began to rebound or stabilize, further complicating the landscape of criminal activity over time [39, 15]. Despite these insights, most existing studies examining these shifts have focused on short time frames, often limited to the early stages of the pandemic [155, 156, 97, 245], and do not capture the full extent of changes across the pandemic timeline. Additionally, while extensive research has examined spatial variability in crime trends at both national and highly localized levels (e.g., streets or districts) [306, 245, 153, 190, 282], there is limited work that explores these dynamics at an intermediate spatial resolution [156, 102, 199]. Addressing these gaps, our study adopts a spatially explicit approach, investigating crime patterns across the pre-pandemic, pandemic, and post-pandemic periods at an intermediate spatial resolution. By capturing regional variations that may be overlooked in national or highly localized studies, our research delivers a comprehensive assessment of the pandemic's long-term effects on crime.

England and Wales provide a particularly relevant case study for our analysis due to their distinct administrative divisions and the availability of detailed crime data. The level of analysis in our study is at the local authority level, which refers to administrative units responsible for governing specific geographic areas, including implementing public safety measures and managing crime prevention strategies [266, 287]. By focusing on local authorities, our research allows for a more precise examination of spatial and temporal variations in crime trends, moving beyond aggregated national data. This approach is particularly valuable for understanding how crime patterns evolved before, during and after the pandemic, as it captures the localized impacts of public health measures and law enforcement practices.

In Chapter 5, we outline our work on analyzing crime trends during the COVID-19 pandemic across local authorities in England and Wales. This includes leveraging publicly available crime data and the lockdown strictness index to examine the relationship between pandemic measures and crime trends. Using advanced spatio-temporal Bayesian modelling, we assess how crime patterns evolved across time and space, providing insights into the differential impacts of lockdown measures on various types of crime. These findings contribute to a deeper understanding of crime dynamics during health crises and offer actionable recommendations for future policy-making.

1.3 Additional Research Contribution: Spatial Analysis of Voter Preferences in France

Here we present a variant of a group project conducted during the first semester of my PhD as part of the "Research Ireland Centre for Research Training in Foundations of Data Science". As part of the programme's structured training model, students engage in an interdisciplinary group project aligned with their research interests. I contributed to a project on the *2017 French Presidential Election*, supervised by Dr. Domijan, Prof. Hurley, Prof. Brunsdon, Prof. Dahyot, and Dr. Mooney. I was primarily responsible for the spatiotemporal modelling of election outcomes. This experience introduced me to a foundational geographic principle—Tobler's First Law of Geography [268]: "everything is related to everything else, but near things are more related than distant things"—and sparked a strong interest in spatial data analysis. Building on this foundation, I revisited the topic independently with my supervisor, Dr. Mooney, to analyse the *2022 French Presidential Election*. This variant project marks a transition toward my own research direction, which later evolved to focus on applying spatiotemporal methods to public health data, including during the COVID-19 pandemic. Our complementary study is presented in Appendix A, where spatial statistical modelling techniques used in this thesis are applied to a different domain. This study investigates the relationship between socio-economic factors and voter preferences in the 2022 French Presidential Election at the departmental level. While distinct from the primary focus of this thesis, it reflects my PhD journey and illustrates the broader applicability of spatial methods and demonstrates how geographic and socio-economic contexts can shape political outcomes.

Understanding voter behavior is a fundamental aspect of political science, yet existing research often fails to account for spatial dependencies in voting patterns, assuming electoral outcomes are independent across regions. However, political preferences are rarely uniform across space; they are influenced by regional economic conditions, and demographic composition, necessitating an approach that explicitly incorporates spatial relationships. To bridge this gap, our study employs a spatially explicit modelling approach, integrating socio-economic indicators such as unemployment rate, poverty rate, higher education rate, and immigration rate to assess their influence on voting patterns across French departments. This methodological framework allows for a more comprehensive understanding of electoral trends by capturing regional effects and socio-economic disparities that traditional models may overlook.

In Appendix A, the analysis of voter preferences in the 2022 French presidential election is presented. In this study, we use publicly available electoral data and socio-economic indicators to examine the relationship between regional disparities and voting behavior at the departmental level. Employing Poisson log-linear regression model with spatial random effects, we assess how socioe-conomic factors influenced electoral outcomes across different regions. This analysis highlights spatial dependencies in voting patterns, demonstrating how localized economic and demographic conditions shape political landscapes.

1.4 Research Aim and Objectives

Having outlined the key knowledge gaps and the focus areas of this thesis, we now state the comprehensive aim and the specific objectives that guide the remainder of the work.

Research Aim: To develop and apply statistically rigorous, spatially explicit, and uncertainty-aware modelling frameworks to quantify *(i)* the effectiveness of pandemic mitigation strategies on mortality, *(ii)* the association between COVID-19 infection and cardiovascular disease increase in older adults across Europe, and *(iii)* the spatiotemporal impacts of pandemic response measures on crime patterns, thereby generating actionable, policy-relevant evidence on population wellbeing during and after COVID-19.

Research Objectives:

- Quantify the effect of lockdowns and vaccination on mortality at county level in Ireland, using a Bayesian hierarchical Poisson regression model with explicit spatial and temporal structure, and construct counterfactual lives saved scenario *(Maps to Chapter 3)*.
- Estimate the association between the odds of developing new-onset CVD and COVID-19 infection among adults 50+ years old across 26 European countries while accounting for other established risk factors, using a Bayesian hierarchical logistic regression model with partial pooling to capture between-country heterogeneity *(Maps to Chapter 4)*.
- Assess how restriction stringency shaped crime dynamics across local authorities in England and Wales (pre-, during, post-pandemic), using a Bayesian spatiotemporal model with seasonal, temporal, spatial dependency, and spatial random effects *(Maps to Chapter 5)*.

- Provide interpretable results, transparent uncertainty quantification with partial information pooling and spatially resolved evidence to support public health and safety decision-making, and identify priorities for preparedness in future crises *(Synthesised in Chapter 6)*.

1.5 Research Contributions

This thesis makes significant contributions to the fields of spatial statistics, epidemiology, and computational social science, advancing both methodological development and the evidence base for policy-oriented understanding of pandemic impacts. The findings extend beyond theoretical modelling to provide data-driven insights and actionable evidence for policymakers seeking to strengthen preparedness, resilience, and targeted interventions in future public health and societal crises.

(1) **County-level evidence on pandemic mitigation strategies (Chapter 3):** This chapter develops a reproducible statistical framework for evaluating pandemic mitigation strategies and offers spatially explicit evidence for Ireland, identifying where lockdowns and vaccination campaigns were most and least effective. The results deliver the first county-level, uncertainty-aware estimates of lives saved, providing critical information for refining regional response strategies in future health emergencies.

(2) **Continental-scale assessment of long-term consequences of COVID-19 infection on cardiovascular health (Chapter 4):** This analysis provides the first Europe-wide, data-driven quantification of how COVID-19 infection increased the odds of developing new cardiovascular disease, revealing vulnerable populations and cross-country disparities. The findings offer valuable guidance for European health agencies and governments in integrating cardiovascular screening and long-term monitoring into post-pandemic recovery and prevention strategies.

(3) **Spatiotemporal analysis of crime trends (Chapter 5):** This study identifies which crime categories rebounded quickly and which remained suppressed following the easing of restrictions, offering a rare longitudinal, data-rich perspective on public safety dynamics during crisis conditions. These insights can inform policing resource allocation, social support planning, and the design of crisis-response strategies for future disruptive events.

(4) **Cross-domain methodological transferability:** The thesis demonstrates that a unified Bayesian spatial and spatiotemporal framework can be effectively applied across diverse domains (e.g. epidemiology (mortality), public health (CVD),

criminology (crime), and socio-political analysis (voting behaviour)). This cross-domain adaptability promotes methodological reuse and reproducibility, showing how uncertainty-aware spatial analysis can enhance decision-making across multiple societal systems.

(5) **Transparency, uncertainty communication, and policy relevance:** Across all chapters, results are presented through posterior means, credible intervals, and uncertainty maps, ensuring clarity and interpretability. This emphasis on transparent uncertainty communication enables decision-makers to assess the confidence and robustness of findings, increasing the usability of results for evidence-based policy. The outputs therefore provide not only statistical inference but also practical, spatially resolved evidence to guide future crisis management under uncertainty.

1.6 Relevant Statistical Learning Methods

The methodological framework of this thesis is grounded in advanced statistical modelling techniques, with a particular focus on Bayesian hierarchical models and spatiotemporal analyses. These approaches facilitate rigorous inference in complex real-world contexts, especially in fields such as public health [253] and social science [312], where data often exhibit sparsity, noise, and intricate hierarchical structures alongside spatial and temporal dependencies. By employing these methodologies, this research seeks to understand spatial patterns and relationships within spatial and multi-level data. The following sections provide a structured overview of the key statistical methods utilized in this study, outlining their core principles and relevance to the research objectives.

1.6.1 Bayesian Inference Framework

In this thesis, statistical models are estimated within a Bayesian inference framework. Bayesian methodology is foundational in statistical modelling due to its ability to integrate prior information and iteratively refine beliefs based on observed data. This approach is grounded in Bayes' theorem, which is mathematically expressed as:

$$\pi(\boldsymbol{\theta} \mid \mathbf{y}) = \frac{\pi(\boldsymbol{\theta})\pi(\mathbf{y} \mid \boldsymbol{\theta})}{\pi(\mathbf{y})} \tag{1.1}$$

where θ represents the model parameters and $y = (y_1, \ldots, y_n)$ denotes the observed data. The components of Bayes' theorem are interpreted as follows:

- $\pi(\theta|y)$ denotes the posterior distribution of the parameters, representing the updated knowledge about θ after incorporating the observed data.

- $\pi(\theta)$ is the prior distribution, encapsulating any pre-existing information or assumptions about θ before the data are observed.
- $\pi(y|\theta)$ corresponds to the likelihood function, describing the probability distribution of the observed data y given the parameters θ.
- $\pi(y)$ represents the marginal likelihood, computed as $\pi(y) = \int \pi(\theta)\pi(y \mid \theta)d\theta$, which integrates the likelihood over all possible values of θ weighted by the prior distribution.

Since $\pi(y)$ does not depend on θ, it can typically be treated as a normalizing constant and omitted when performing inference. This simplifies the expression to:

$$\pi(\theta \mid y) \propto \pi(\theta)\pi(y \mid \theta). \tag{1.2}$$

This formulation highlights how Bayesian inference systematically updates prior beliefs by incorporating empirical evidence, making it particularly valuable for modelling complex data structures and quantifying uncertainty in parameter estimates [27, 108].

1.6.2 Hierarchical Models

Hierarchical modelling leverages the inherent grouping structure within data to improve the estimation of related parameters by introducing structured dependencies across multiple levels. Typically, these parameters share probabilistic relationships dictated by the underlying structure of the problem. For instance, in datasets with geographic attributes, local regions may be nested within countries, which in turn belong to broader continental groupings. The primary objective of hierarchical modelling is to construct a joint probability framework that accurately represents these nested relationships [17].

This approach is particularly valuable when dealing with sparse datasets, as it enables information pooling across different levels of hierarchy [284]. By incorporating information from higher-level groupings, the model generates well-informed hyper-parameter estimates, which subsequently refine the estimates at lower levels where data may be limited. This is especially important in spatial applications and multi-level data, where data scaricity can otherwise lead to high variance or biased estimates. Within this thesis, hierarchical modelling is applied to exploit the geographic structure of the datasets. By aggregating information across sub-national regions, countries, and sub-continental divisions, the methodology ensures more robust parameter estimation, even in cases where direct observations are scarce at finer spatial scales.

1.6.3 Bayesian Spatial Models

Bayesian hierarchical models, such as those described by Banerjee et al. [16], are widely used in the analysis of areal data, where observations are recorded for specific geographic areas [191]. Examples include mortality counts per region [227, 151], crime incidents in small scale [228, 233], the average increase in CVD risk across European countries [226], or the number of votes per candidate in each department [225]. These models allow for a structured framework for accounting for spatial heterogeneity, integrating covariates, and modelling unobserved dependencies [191].

A fundamental concept in spatial statistics is *spatial autocorrelation*, which describes the extent to which values of a variable exhibit similarity across nearby locations. The presence of spatial autocorrelation underscores the need for statistical models that explicitly incorporate spatial dependence, ensuring more accurate inference and improved predictive performance. Bayesian hierarchical modelling strategy accommodates spatial autocorrelation, facilitates the assessment of covariate effects, and provides coherent uncertainty quantification.

A well-established used spatial model in this context is the Besag-York-Mollié (BYM) model [29]. Suppose that Y_i denotes the observed outcome in region i for $i = 1, \ldots, n$, and is assumed to follow a Normal distribution:

$$Y_i \sim \text{Normal}(\mu_i, \sigma^2), \tag{1.3}$$

$$\mu_i = \mathbf{z}_i \boldsymbol{\beta} + u_i + v_i. \tag{1.4}$$

Here, $\mathbf{z}_i = (1, z_{i1}, \ldots, z_{ip})$ is the covariate vector for region i, and $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_p)$ represents the corresponding regression coefficients. The model includes two types of random effects: a spatially structured term u_i, and an unstructured term v_i. The spatial component u_i captures dependence across neighboring regions, acknowledging that geographically proximate areas may exhibit similar outcomes. It is typically modeled using an intrinsic Conditional Autoregressive (CAR) prior, where each u_i is drawn from a Normal distribution centered on the average of its neighbors:

$$u_i | u_{-i} \sim N\left(\bar{u}_{\delta_i}, \frac{\sigma_u^2}{n_{\delta_i}}\right), \tag{1.5}$$

with $\bar{u}_{\delta_i} = n_{\delta_i}^{-1} \sum_{j \in \delta_i} u_j$, where δ_i denotes the set of neighbors of region i, and n_{δ_i} is the number of such neighbors. The unstructured component v_i is typically modelled as independent and identically distributed normal noise with mean zero and variance σ_v^2, capturing residual variation unrelated to spatial structure, such that $v_i \sim N(0, \sigma_v^2)$ [191].

Bayesian Inference and Computational Methods

Bayesian inference provides a principled framework for parameter estimation by updating prior distributions with observed data using Bayes' theorem. This approach is commonly used for hierarchical and spatial models, where accounting for uncertainty and incorporating prior knowledge are essential. In most practical applications, the posterior distribution of the parameters is not available in closed form, necessitating the use of numerical approximation techniques.

Among the most widely adopted computational approaches for Bayesian inference in hierarchical models or spatial model are Integrated Nested Laplace Approximation (INLA) [241] and Markov Chain Monte Carlo (MCMC) methods [106], with JAGS (Just Another Gibbs Sampler) [220] being a well-known implementation of the latter.

- **INLA**: INLA is a computationally efficient method designed for latent Gaussian models, a broad category that includes generalized linear mixed models, spatial models, and spatiotemporal models [241, 191]. Instead of relying on traditional MCMC sampling, INLA employs a combination of analytical approximations and numerical integration to approximate posterior distributions. This makes it significantly faster than MCMC-based methods, particularly for large datasets and high-dimensional models. Its speed and accuracy make INLA particularly useful for applications such as disease mapping, ecological modelling, and spatiotemporal forecasting. However, its primary limitation lies in its specificity to latent Gaussian models, making it less flexible when dealing with highly non-Gaussian or non-standard model structures.

- **JAGS and MCMC-Based Methods**: JAGS is a widely used tool for Bayesian inference that utilizes MCMC sampling, specifically Gibbs sampling, to estimate posterior distributions [220]. It allows for the fitting of hierarchical models where analytical solutions are impractical. JAGS follows the BUGS (Bayesian Inference Using Gibbs Sampling) model specification language, making it compatible with other Bayesian modelling software such as WinBUGS and OpenBUGS. Unlike INLA, which is optimized for specific model structures, JAGS offers greater flexibility, allowing for more complex models, including those with non-Gaussian distributions and non-linear dependencies. However, MCMC-based methods such as JAGS tend to be computationally expensive, often requiring long sampling runs to ensure convergence, particularly in high-dimensional parameter spaces.

While both INLA and JAGS serve as powerful tools for Bayesian inference, they each have their advantages and limitations: 1) INLA is computationally efficient and particularly well-suited for latent Gaussian models, making it preferable when speed is a critical factor. 2) JAGS, based on MCMC, offers greater modelling flexibility, accommodating more complex structures beyond latent Gaussian models.

Given the nature of the datasets used in this thesis, which include spatial and hierarchical structures, both INLA and JAGS are considered as computational tools. INLA is utilized for efficiently estimating parameters in latent Gaussian models, as demonstrated in Chapter 5 and Appendix A, whereas JAGS is applied in cases requiring greater flexibility in model specification, such as in Chapter 3 and Chapter 4. The choice of method is determined based on model complexity, computational feasibility, and the need for accurate posterior estimation.

1.7 Outline of the Thesis

This thesis is organized as follows:
Chapter 2 provides a detailed account of the datasets, preprocessing procedures, modelling rationale, and computational tools that underpin the analyses conducted in the following empirical chapters. By outlining the data and variable selection criteria, and methodological framework in a unified manner, this chapter establishes the technical foundation and ensures transparency and reproducibility across all studies. Chapter 3 evaluates the effectiveness of pandemic mitigation strategies namely lockdowns and vaccination efforts on mortality across Ireland using a Bayesian Hierarchical Poisson Regression model. In this context, it is important to note that the county-level "number of lives saved" (see Figure 3.3) map reproduced in Chapter 3 is an updated and corrected version of the figure originally published in Pourshir Sefidi et al. [227]. The published version contained a plotting error arising from a retired R package (rgdal) that misaligned some county polygons, but the underlying numerical model outputs were correct and are unchanged; the corrected map in the thesis should therefore be regarded as the authoritative version of this result. Chapter 4 investigates the long-term cardiovascular consequences of COVID-19, applying a Bayesian hierarchical logistic regression framework to data from 26 European countries, with a focus on vulnerable populations. Chapter 5 explores the pandemic's societal impacts by analyzing shifts in crime trends across local authorities in England and Wales, leveraging spatiotemporal Bayesian modelling techniques. Chapter 6 concludes the thesis by revisiting the research aims and objectives, synthesizing the key findings, discussing their broader implications and impacts, and outlining potential avenues for future research.

2

Datasets, Preprocessing, and Modelling Framework

2.1 Introduction

This chapter describes the datasets, preprocessing procedures, modelling frameworks, and computational tools employed throughout the thesis. It is structured to promote transparency and reproducibility, providing detail to replicate the data preparation, model development, and implementation steps presented in Chapters 3 to 5. The rationale for dataset and model selection is discussed, along with the data exploration and variable selection/transformation undertaken for each study and the key analytical toolkits used.

Each study uses available datasets and implements Bayesian hierarchical and spatiotemporal modelling frameworks, chosen for their flexibility in handling multilevel, spatially dependent data and for their ability to communicate uncertainty effectively in policy-relevant contexts.

2.2 Dataset Selection and Description

2.2.1 Criteria for Dataset Selection

Datasets were selected according to the following criteria:

- Openly accessible, or obtainable through approved data access requests.
- Sufficient spatial and temporal resolution to capture relevant local, national, and temporal variation.
- Accompanied by comprehensive documentation and metadata.
- Consistent with official statistical or scientific sources.
- Previously used in peer-reviewed or policy-relevant studies, ensuring reliability and comparability.

Datasets for the "Effectiveness of Pandemic Mitigation Strategies" Study

The study in Chapter 3 focuses on quantifying the effect of lockdowns and vaccination on COVID-19 mortality in Ireland. For this purpose, the following variables and associated data sources were used:

- **Mortality data:** Instead of relying on daily COVID-19–specific death counts, we used all-cause mortality data due to the lack of reliable, real-time cause-specific records [151]. COVID-19 mortality data during the early phases of the pandemic were subject to potential misclassification, depending on the certifying practitioner [179]. Typically, mortality data from the Central Statistics Office (CSO) are used for such analyses; however, in Ireland, particularly during the first phase of the pandemic, the official data reporting process was slow, often with delays of up to three months, and cases requiring additional investigation took even longer to be finalized. Therefore, we employed an auxiliary data source providing near–real-time mortality trends as a proxy for all-cause mortality when official records lagged behind. These data were derived from *daily* and *town*-level death notices scraped from `https://rip.ie/`. Although this source has some inherent biases, for instance, potential undercounting due to the omission of deaths among tourists, international students, immigrants, temporary workers and children, it remains a valuable resource [182]. Notably, the CSO itself has also adopted this source to supplement its official mortality reporting [56], and it has also been used by other researchers [76, 124].

- **COVID-19 cases:** Confirmed COVID-19 case counts were obtained from Ireland's COVID-19 Data Hub, which provides *county*-level and *daily* data. The Data Hub provides information from the Health Protection Surveillance Centre (HPSC) and the Health Service Executive (HSE), making it a reliable and authoritative source of COVID-19 surveillance data [206] and been used in studies by Gleeson et al. [110], Bennett et al. [25].

- **Vaccination rates:** Vaccination data were sourced from the CSO of Ireland, providing cumulative doses administered by *local electoral area* on a *monthly* basis. These data have been used in previous studies [175, 310].

- **Government response:** Government policy measures were captured using the Oxford COVID-19 Government Response Tracker (OxCGRT) Stringency Index, which provides *daily*, *country*-level data. The OxCGRT systematically records, in real time, all COVID-19–related regulations and policy interventions introduced throughout the pandemic [218].

- **Environmental covariates:** *Monthly* average temperature data at the *town*-level were obtained from Met Éireann to account for potential seasonal influences on mortality [135]. Met Éireann is Ireland's National Meteorological Service and the state's primary provider of weather and climate information, and is officially recognised by the World Meteorological Organization (WMO). Data provided by Met Éireann have been widely used in previous research studies [41, 72].

Datasets for the "Long-Term Health Consequences: COVID-19 and Cardiovascular Disease" Study

The next study, Chapter 4, used data from the *Survey of Health, Ageing and Retirement in Europe* (SHARE) Waves 8 and Corona Surveys (SC1 and SC2). We applied for and obtained formal permission to access these data through the SHARE Research Infrastructure. The dataset includes harmonised information on individuals aged 50+, with detailed records on socio-demographics, health behaviours, and chronic conditions, among other variables. SHARE has been widely used in European health and ageing research (e.g., Hussain et al. [136], Enescu and Răileanu Szeles [87], Tur-Boned et al. [273], and Grané et al. [114]). Its standardised design allows cross-country comparability, making it ideal for macro-level Bayesian hierarchical modelling.

Variables used included:

- **COVID-19 infection status:** Binary self-reported variable indicating whether the respondent had a COVID-19 infection.

- **Cardiovascular disease:** Indicator of newly reported or worsened CVD following COVID-19 infection.

- **Risk factors:** Hypertension, diabetes, and chronic lung disease (all binary variables), along with body mass index (BMI; continuous variable), were included as covariates because they are well-established risk factors for cardiovascular disease (CVD) [99, 161, 48, 5].

- **Socio-demographic controls:** Age, sex, and country.

Datasets for the "Crime Trends During the COVID-19 Pandemic" Study

The third study (Chapter 5) analysed crime data across local authorities in England and Wales.

- **Crime data:** The police forces in England and Wales record and report spatially referenced data on criminal activities at a *monthly* frequency and at the *Lower Layer*

Super Output Area (LSOA) level. These statistics are publicly available through the Police UK website (`https://data.police.uk/`) and classify crimes into twelve distinct categories. Data from this source were used in the study in Chapter 5, and it has also been widely employed in previous research as a reliable and authoritative source of crime information in longitudinal and spatial analyses (e.g., Halford et al. [122], Langton et al. [156, 155], and Frith et al. [97]).

- **Government response:** Stringency Index was used as a proxy for restriction intensity at the *daily* and *country* levels. However, although England and Wales are administratively distinct countries, the OxCGRT reports a single value for the entire United Kingdom; therefore, the stringency index was identical for both England and Wales.

2.3 Data Exploration, Wrangling, and Variable Selection

2.3.1 Data Cleaning and Integration

All datasets were systematically examined for missingness, outliers, and both temporal and spatial inconsistencies before analysis. Records with missing values were removed rather than imputed, as imputation could introduce artificial spatial or temporal autocorrelation and bias the results, particularly where missingness was non-random. For instance, in the crime dataset used in Chapter 5, data for Greater Manchester were excluded entirely due to persistent missing records following changes in police IT reporting systems. Similarly, other sporadically incomplete observations were omitted to preserve the integrity of spatial dependencies and temporal continuity across all studies. This approach ensured that the statistical inferences derived from the models reflected genuine observed patterns rather than artefacts of data reconstruction.

Geographic identifiers were standardised and harmonised across datasets within each study to facilitate accurate spatial merging with corresponding shapefiles, proportionate to each study's geographic scope (e.g., counties in Ireland (Chapter 3), countries in Europe (Chapter 4), and local authorities in England and Wales (Chapter 5)). Temporal alignment checks were also performed to ensure consistent monthly or yearly aggregation across all variables prior to modelling, maintaining comparability between data sources.

2.3.2 Variable Selection and Transformation

To facilitate modelling, new variables were derived and existing ones were harmonised across datasets in each study, ensuring consistent temporal and spatial resolution. Because the datasets differed in granularity, the variable transformation process was adapted to the scope and data structure of each analysis.

For the study presented in Chapter 3, all variables were aligned to the coarsest shared resolution of monthly and county level. Variables available at finer temporal or spatial resolutions were aggregated accordingly. Specifically, mortality counts and confirmed COVID-19 case counts were summed by month and county, while variables such as lockdown severity (Stringency Index) were averaged over each month to reflect mean restriction intensity. Vaccination rates and temperature were retained at their original monthly resolution, as they were already the limiting variables in terms of temporal granularity.

In the study described in Chapter 4, conducted using the SHARE dataset, several derived binary indicators were created to facilitate modelling. Binary variables were generated for COVID-19 infection status, hypertension, diabetes, chronic lung disease, and incident CVD onset. In addition, continuous variables for age and BMI were computed directly from the raw survey data: age was calculated by subtracting each respondent's birth year from the year of the survey, while BMI was obtained by dividing self-reported weight in kilograms by height in meters squared ($\text{BMI} = \frac{\text{weight (kg)}}{\text{height (m)}^2}$). These transformations ensured consistent and interpretable covariates across the 26 European countries included in the analysis.

For the study in Chapter 5, all covariates were harmonised at the monthly and local-authority level. To match the temporal resolution of the crime dataset, the Stringency Index values were averaged for each month to represent the mean level of pandemic restriction intensity. All continuous predictors were then normalised or standardised (z-scores) to enable comparability of coefficients across different scales.

Together, these variable transformation steps ensured that each dataset was internally consistent, aligned in resolution, and optimised for integration within the chosen modelling frameworks.

2.3.3 Data Validation and Exploration

Comprehensive exploratory data analysis was carried out for all studies to evaluate data quality, assess relationships among variables, and identify patterns that could inform model specification. Descriptive statistics, pairwise correlations, and temporal trend visualisations were produced to examine variable distributions and detect potential anomalies or inconsistencies. Spatial exploratory analysis included the creation of choropleth maps using the `ggplot2` packages in R, which revealed clear geographic clustering across the study regions. These visual inspections helped verify that the observed spatial patterns were plausible and consistent with prior expectations based on demographic or socio-economic structures.

For model diagnostics, preliminary residual analyses were conducted to check for un-modelled spatial structure and potential temporal autocorrelation. Residual maps confirmed significant spatial dependence in all datasets, validating the subsequent use of spatially explicit hierarchical and spatiotemporal models. This stage of validation ensured that the data were internally coherent, appropriately structured for analysis, and suitable for the modelling frameworks applied in later chapters.

2.4 Modelling Framework and Rationale

2.4.1 Criteria for Model Selection

The modelling frameworks were selected to satisfy four key criteria:

(1) Handle hierarchical and spatially correlated data.

(2) Quantify uncertainty through posterior distributions.

(3) Enable partial pooling to stabilise estimates for small areas or sparse data.

(4) Offer interpretability for policy communication.

2.4.2 Model Descriptions

Bayesian Poisson Regression (Chapter 3). To estimate the impact of lockdowns and vaccination on COVID-19 mortality in Ireland, a Bayesian Poisson regression model was used. Let Y_{it} denote the number of deaths in county i and month t. The model assumes:

$$Y_{it} \sim \text{Poisson}(\lambda_{it}), \quad \log(\lambda_{it}) = \mathbf{x}_{it}\boldsymbol{\beta}.$$

Here, $\mathbf{x}_{it}$ includes explanatory variables such as the Stringency Index, vaccination rate, confirmed COVID-19 cases, temperature, and a linear time trend. No explicit random effects were introduced; instead, uncertainty was propagated through the posterior distributions of coefficients, allowing for fully probabilistic inference. Posterior samples were used to compute counterfactual death estimates by setting policy-related covariates (stringency and vaccination) to zero.

Bayesian Logistic Regression (Chapter 4). To examine the relationship between COVID-19 infection and the risk of developing cardiovascular disease across Europe, a Bayesian logistic regression model was used. For individual i in country j,

$$Y_{ij} \sim \text{Bernoulli}(p_{ij}), \quad \text{logit}(p_{ij}) = \mathbf{x}_{ij}\boldsymbol{\beta},$$

where $\mathbf{x}_{ij}$ includes indicators for COVID-19 infection, hypertension, diabetes, chronic lung disease, BMI, age, and sex. The model estimated continent-level effects of infection and comorbidities without incorporating country-level random intercepts; country differences were captured through fixed country indicators. This formulation allowed clear interpretation of posterior odds ratios across Europe.

Bayesian Spatiotemporal Poisson Model (Chapter 5). The crime study required explicit spatial and temporal structure. For local authority i and month t,

$$Y_{it} \sim \text{Poisson}(\lambda_{it}), \quad \log(\lambda_{it}) = \mathbf{x}_{it}\boldsymbol{\beta} + u_i + v_t + \epsilon_{it}.$$

Here, u_i captures spatial dependence through a CAR prior, v_t represents temporal trends, and ϵ_{it} is unstructured noise. This specification enabled identification of region-specific responses to lockdown stringency and temporal recovery trajectories.

2.4.3 Parameter Settings and Priors

Across all Bayesian hierarchical and spatial models, priors should be chosen carefully to balance regularisation with realism. In most cases, weakly informative priors were adopted so that inference was primarily data-driven while avoiding unstable or implausible estimates. Throughout this thesis, fixed-effect coefficients were typically assigned $\text{Normal}(0, 1)$ priors, and precision parameters followed $\text{Gamma}(1, 0.01)$ distributions. Spatial random effects were modelled using CAR priors, which encourage smoothing between neighbouring regions while retaining local variation. In certain instances, informative priors were specified to incorporate realistic domain knowledge from previous studies where data limitations or biases were known to exist. For example, in Chapter 3, an informative prior was defined for the number of confirmed COVID-19 cases during the first seven months of the pandemic, a period characterised by widespread underreporting due to limited testing capacity. Including this prior helped stabilise early trend estimates and produced a more plausible reconstruction of initial outbreak dynamics. Informative priors of this nature were used selectively and only when supported by empirical or contextual evidence. At higher levels of the model hierarchy, uninformative or weakly informative hyperpriors were used for the group-level parameters to allow sufficient flexibility without imposing restrictive assumptions. For each group j, the mean parameter μ^j was given a $\text{Normal}(0, 10)$ prior, and the corresponding standard deviation parameter σ^j followed a positive-truncated Student-t distribution $\text{StudentT}^+(0, 1, 1)$. These hyperpriors are commonly used in hierarchical Bayesian models because they provide broad support for plausible parameter values while ensuring numerical stability during sampling.

Following model estimation, convergence and mixing of posterior samples were assessed using trace plots and the Gelman–Rubin diagnostic ($\hat{R} < 1.05$). These diagnostics confirmed that the posterior distributions were well behaved and that inferences drawn from them were reliable.

2.4.4 Alternative Modelling Approaches

Alternative methods considered included:

- **Frequentist mixed-effects models** – appropriate for hierarchical data but less capable of full uncertainty propagation.
- **Geographically Weighted Regression (GWR)** – models spatial heterogeneity but does not easily incorporate temporal structure or hierarchical levels.
- **Machine-learning methods** (e.g., random forest, XGBoost) – strong predictive performance but limited interpretability for policy contexts.

The Bayesian hierarchical framework was therefore chosen for its interpretability, flexibility, incorporation of prior information, and principled quantification of uncertainty.

2.5 Computational Implementation and Toolkits

All analyses were performed in R (version 4.5.1). Key toolkits included:

- `R-INLA` (version 24.12.11) for latent Gaussian models.
- `rjags` (JAGS 4-17) for Bayesian sampling.
- `sf`, `sp`, and `ggplot2` for spatial operations and mapping.
- `dplyr`, `tidyverse`, and `lubridate` for data wrangling.
- `ggplot2` and `ggpubr` for visualisation and diagnostics.

All code and workflows, from data acquisition and cleaning to model fitting and output generation, were version-controlled using GitHub and are available in the GitHub repositories referenced for each study at `https://github.com/nilips70`.

2.6 Summary

This chapter outlined the datasets, data preparation procedures, modelling rationale, and computational tools supporting this thesis. All datasets were selected for their accessibility, quality, and relevance, and underwent thorough cleaning and validation. The chosen Bayesian and spatiotemporal models enable robust handling of structured data and transparent uncertainty quantification. Together, these foundations ensure that the analyses presented in Chapters 3–5 are transparent, reproducible, and extendable.

3 The Effectiveness of Pandemic Mitigation Strategies

Publication and Author Contributions

This chapter is based on the published article:

> Pourshir Sefidi, N., Shoari Nejad, A., Mooney, P., An investigation of the effects of lockdowns and COVID-19 vaccinations in Ireland. *26th AGILE Conference on Geographic Information Science "Spatial data for design", Delft, The Netherlands*, AGILE: GIScience Series 4 (2023): 37. `https://doi.org/10.5194/agile-giss-4-37-2023`

This study was conducted collaboratively; however, I led all major aspects of the research. I was primarily responsible for the study design, data collection and preprocessing, model development and implementation, statistical analysis, and preparation of the manuscript. My co-authors provided supervisory guidance, methodological advice, and editorial feedback. The content presented here is consistent with the published version, with minor edits for coherence within the thesis.

One important clarification is that the county-level "number of lives saved" map reproduced as Figure 3.3 in this chapter has been regenerated using an updated R spatial data pipeline. The original publication relied on a now-retired rgdal package, which subsequently led to a misalignment between some county polygons and the underlying numerical results. The Bayesian model estimates reported in the original paper were always correct and remain unchanged; the corrected map presented in this thesis should therefore be regarded as the authoritative graphical representation of those results.

Summary of Key Contributions

- Developed a Bayesian Hierarchical Poisson Regression (BHPR) model to estimate the impact of lockdowns and vaccinations on COVID-19 mortality.

- Analysed publicly available data from 2020 to 2022 to assess trends and quantify intervention effectiveness.
- Conducted counterfactual simulations, estimating that 16,876 lives (95% CI: 13,799–20,140) were saved due to lockdowns and vaccination efforts.
- Examined county-level variations, identifying differences in the effectiveness of public health measures across Ireland.
- Demonstrated the utility of hierarchical Bayesian modelling for epidemiological research and the evaluation of policy interventions.

3.1 Introduction

The COVID-19 pandemic, which begun in early 2020 is one of the most globally impactful events in recent memory. No continent, country, or region remained untouched by the effects of the pandemic. At the end of December 2022, over 8,250 people in Ireland had died from COVID-19 infection [83, 293]. At the time of writing, COVID-19 is still circulating and causing illness and fatalities in many countries. Mutations of this virus arise and continue lead to the emergence of new variants of concern [83]. In the early days of the pandemic, without a vaccine or pharmaceutical treatment, efforts to contain the spread of COVID-19 focused on isolation measures for confirmed cases and self-quarantine for those who had been exposed. However, due to the high transmissibility of the virus, including spread from asymptomatic cases, these measures were not sufficient alone to fully contain the spread [149]. Pandemic response measures, such as closing schools, public spaces, and non-essential businesses, were also implemented in an effort to reduce social interaction and opportunities for person-to-person transmission. The intended impact was to reduce the risk of overwhelming health systems and allowing more time for the development of effective treatments and vaccines [148, 148, 162]. As we know now a number of vaccines against Coronavirus were developed and subsequently deployed. The vaccination effort in Ireland started in December 2020 [203] with the overall goal of reducing the COVID-19 mortality rate in the country. Finding the answers to what approaches worked best during the pandemic is not easy. There is an ongoing debate among epidemiologists about the effectiveness of physical distancing measures and the efficacy of vaccines while many mathematical models have been created to predict impacts from the pandemic on health systems and national economies [125]. The implementation of pandemic response measures and the vaccination timeline have differed among countries. We believe that it is essential to assess the impact of both lockdowns and vaccination campaigns in order to inform the future development of evidence-based strategies for protecting people from a contagious virus such as COVID-19.

3.1.1 Related Literature

There is significant existing literature in this domain of study. Many epidemiologists have attempted to understand the impact of pandemic responses on mortality rates. Studies have suggested that many lives have been saved as a result [20]. Some studies, like the one conducted by Chaudhry et al. [57], found no connection between the level of lockdown measures and COVID-19 death rates. In a separate study by Born et al. [31], the authors used a synthetic control method to suggest that Sweden's decision not to implement widespread lockdown measures did not significantly contribute to its COVID-19 death cases. Other studies, such as Atkeson et al. [10], Medica [183], and De Larochelambert et al. [73], also found no significant differences in mortality rates among different pandemic responses and population density. These findings challenge the widely held belief that pandemic responses are effective at controlling the spread of the virus. In contrast, other researchers, such as Figueiredo et al. [95], Lau et al. [157], have found that pandemic measures are important and effective in reducing the likelihood of contagion and the spread of the COVID-19, based on the time-series analysis of confirmed cases in China. With the development of a mathematical model of COVID-19 transmission, Watson et al. [283] found that vaccinations prevented an estimated 14.4 million COVID-19 deaths in 185 countries and territories between December 2020 and December 2021. Liang et al. [164] conducted a regression analysis with a country-level random effect and found evidence supporting the importance of vaccination in preventing deaths among infected individuals. They also emphasized the significance of achieving consistent vaccine coverage to effectively translate the benefits of vaccines into desired public health outcomes. According to Jabłońska et al. [140] who used a non-linear Poisson mixed regression model, COVID-19 vaccination coverage (the proportion of COVID-19 vaccinated inhabitants in an area) is effective at decreasing mortality in European countries and Israel. In addition to this, the study also found that reducing mobility within and between countries is effective at reducing COVID-19 mortality and suggests that there may be seasonal variations in COVID-19 incidence.

3.1.2 Contribution of this Research

We believe it is very important to thoroughly test the effectiveness of pandemic measures and vaccination rates on mortality. As described above in section 3.1.1 there have been several studies on this topic. However, to the best of our current knowledge, no research has specifically evaluated the impact of these measures and vaccination rates on mortality within Ireland. The aim of this research is to fill this knowledge gap for Ireland. In this work we investigate the effects of: lockdowns strictness, COVID-19 confirmed cases, and vaccination rate on overall mortality in Ireland. More precisely, we attempt to estimate the number of lives that lockdown and vaccination efforts have saved in Ireland since the start of the COVID-19 pandemic. The data used in our study are available publicly and the references to these datasets are provided below. As mentioned in the previous section, existing works have implemented different modelling frameworks including: Spatial Autoregressive (SAR), Geographically Weighted Regression (GWR), and Bayesian Spatially Varying Coefficient Model, to capture the spatial variation in the factors that impact mortality [256, 70, 151] from COVID-19. In our work, we present a Bayesian Hierarchical Poisson Regression (BHPR) model that allows us have both county-level effects (administrative regions within the country of Ireland) and also country-level effects to capture both spatial variations and estimate the overall effects at the country level. Ireland is divided into counties which have administrative and governance responsibilities for specific matters (taxation, housing management, road and environmental management, and so on). Very often in Ireland, public health services are organised around county-level approaches. Indeed, in some cases, public health services may combine several counties into one management region. There are 26 counties in the Republic of Ireland with 6 counties in Northern Ireland. This work applies only to the counties within the Republic of Ireland as there were different public health strategies pursued in the Republic and Northern Ireland during the time periods of this study. Additionally, health services in the 6 counties in Northern Ireland are managed by the government in Northern Ireland and the UK.

Our results show that there are variations among the counties of Ireland with respect to the effectiveness of lockdowns and vaccination. At the country level, we show that both of these factors resulted in an overall reduction in mortality from COVID-19. Furthermore, we attempted to calculate the number of deaths if there were no vaccination and lockdowns in order to estimate the number of lives saved by these actions. We estimated the number to be $16,876$ (CI: $13,799$ - $20,140$). The goodness of fit of our model is measured by $R^2 = 0.98$, which indicates an overall good performance.

In summary, this work provides some evidence indicating that the use of lockdowns and vaccination efforts in Ireland were effective in reducing mortality. Furthermore, we suggest the BHPR model is a suitable candidate for use in studying the effects of various factors on mortality for the following reasons:

- The BHPR model provides a flexible framework for modelling count data which is often encountered in mortality studies.
- The BHPR model can handle complex data structures including data with multiple levels, such as country and sub-country levels.
- The approach can take advantage of *information pooling*. This is an important feature of the hierarchical models. Information pooling refers to the sharing of information across different levels of the model and this information can improve parameter estimation and reduce uncertainty. In the context of this study, this means that information from different counties or regions can be combined to obtain more accurate estimates.
- The Bayesian framework allows prior information to be incorporated into the model and this can improve parameter estimation and reduce uncertainty.
- The model framework provides a more natural way to quantify uncertainty in model

estimates. Quantification of uncertainty is important for making informed decisions and drawing valid conclusions from the subsequent analysis.

The remainder of the chapter is structured as follows. In section 3.2 we describe the overall methodology including a discussion of the data requirements (section 3.2.1) and the modelling procedure used (section 3.2.2). Section 3.3 outlines some of the key results of this work. Section 3.4 is the penultimate section of the study and provides some concluding remarks and ideas for future work.

3.2 Our Methodology and Approach

In this section, we carefully describe the data used in our analysis (section 3.2.1) and then proceed to describe the modelling framework and procedure we followed to build the BHPR model (section 3.2.2).

3.2.1 Data Requirements

For this work, we aimed at investigating the impact of lockdown strictness and vaccination rate on mortality during the COVID-19 pandemic period (2020-2022). However, we have used data from during the period 2016 to 2022 in order to better estimate the non-pandemic related effects, such as weather temperature, and to also better understand the overall time trend. To examine the effect of these factors, we have used five data sources:

(1) **Temperature:** As temperature is associated with mortality [251], we retrieved data on the monthly average temperature in Ireland from 2016-2022 from the website of Met Éireann, Ireland's National Meteorological Service [261].

(2) **All-causes mortality:** The data on all-cause deaths at a town level for each day was obtained from the `RIP.ie` website [1] which is widely considered one of the most reputable sources of bereavement information in Ireland [54]. The data includes the surname, date of death, and location for each bereavement notice. Having the date of the notice and the county name associated with each location we calculated the number of monthly deaths for each county in Ireland by taking the total number of the notices within each county on a monthly basis.

(3) **COVID-19 vaccination rate:** Since January 2021, the Central Statistics Office of Ireland (CSO) [55] has provided the monthly cumulative proportion of COVID-19 vaccinated inhabitants at the local electoral area (LEA) level. We calculated the monthly cumulative vaccination rate for each county by aggregating the LEAs (with each county) cumulative vaccination rates.

(4) **Confirmed COVID-19 cases:** Daily data on new confirmed cases of COVID-19 at the county level in Ireland is available from Ireland's COVID-19 data hub [127]. We calculated the monthly total of confirmed cases for each county using this data source.

(5) **Government Response Oxford Stringency Index:** The Oxford Stringency Index (SI) measures the strictness of physical distancing and lockdown-style policies that primarily restrict people's behaviour [121]. The SI is calculated using various containment and closure policy indicators. As well as being an indicator for public information campaigns it is reported daily at the country level. It is a numerical scale ranging from 0 to 100, with 0 indicating the loosest restrictions and 100 indicating the strictest. In our study, the monthly SI values were calculated by taking the monthly averages of the index to match the temporal resolution of other variables used in this study.

3.2.2 Modelling Procedure

In this section, we explain the modelling framework that we followed to build the BHPR model. We denote $y_{t,k}$ as the number of deaths at time t where $t = 1, 2, \ldots, 79$ (from January 2016 to August 2022) and county $k(k = 1, 2, ..., 26)$. We write the model hierarchically as follows:

$$y_{t,k} \sim Poisson(\lambda_{t,k}) \tag{3.1}$$

where $\lambda_{t,k}$ is the average mortality at month t and county k, and it is modelled as:

$$\begin{aligned} log(\lambda_{t,k}) = \alpha_k &+ \beta_k^{SI} \times SI_t + \beta_k^{temp} \times temperature_t \\ &+ \beta_k^{case} \times case_{t,k} \\ &+ \beta_k^{int} \times cases_{t,k} \times vaccination_{t,k} \\ &+ \beta_k^{trend} \times t \end{aligned} \tag{3.2}$$

where α_k is the county-level intercept, β_k^{SI} is the county-level effect of the stringency index, β_k^{temp} is the county-level effect of temperature, β_k^{case} is the county-level effect of confirmed cases, β_k^{int} is the county-level effect of the interaction between confirmed cases and vaccination rate, β_k^{trend} is the county-level effect of time. We add the country-level effects to the model as hierarchical priors on the county-level effects as follows in Equation 3.3. For brevity we denote β_k^i as the i^{th} effect in county k.

$$\beta_k^i \sim Normal(\mu^i, \sigma^i) \tag{3.3}$$

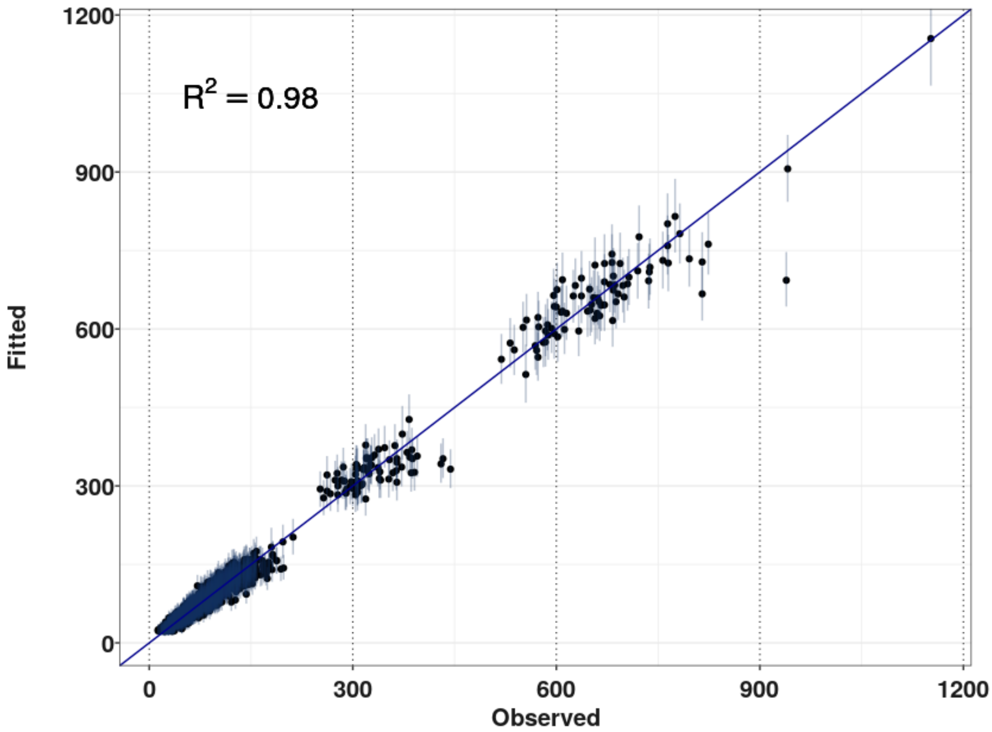


Figure 3.1: Comparison of predicted values from the model to actual death count in counties of Ireland from 2016 to 2022. The 95% uncertainty intervals are depicted by vertical bars.

where μ^i represents the country-level effect of the effect i with σ^i representing the country-level standard deviation of the effect i. Below we show the non-informative hyperpriors used:

$$\begin{aligned} \mu^i &\sim Normal(0, 10) \\ \sigma^i &\sim StudentT(0, 1, 1)^+ \end{aligned} \tag{3.4}$$

During the early stages of the pandemic, due to lack of widespread testing, there is great uncertainty about the true number of cases. Different sources have reported different figures from 7 to 12 times the reported cases [234, 184, 4]. Taking a sensible and pragmatic approach to this issue, we do not consider the number of cases during the first seven months of 2020 as fixed. Instead, to account for the uncertainty, we assume that they are subject to a distribution that can be inferred along with the other parameters of the model as outlined here in Equation 3.5:

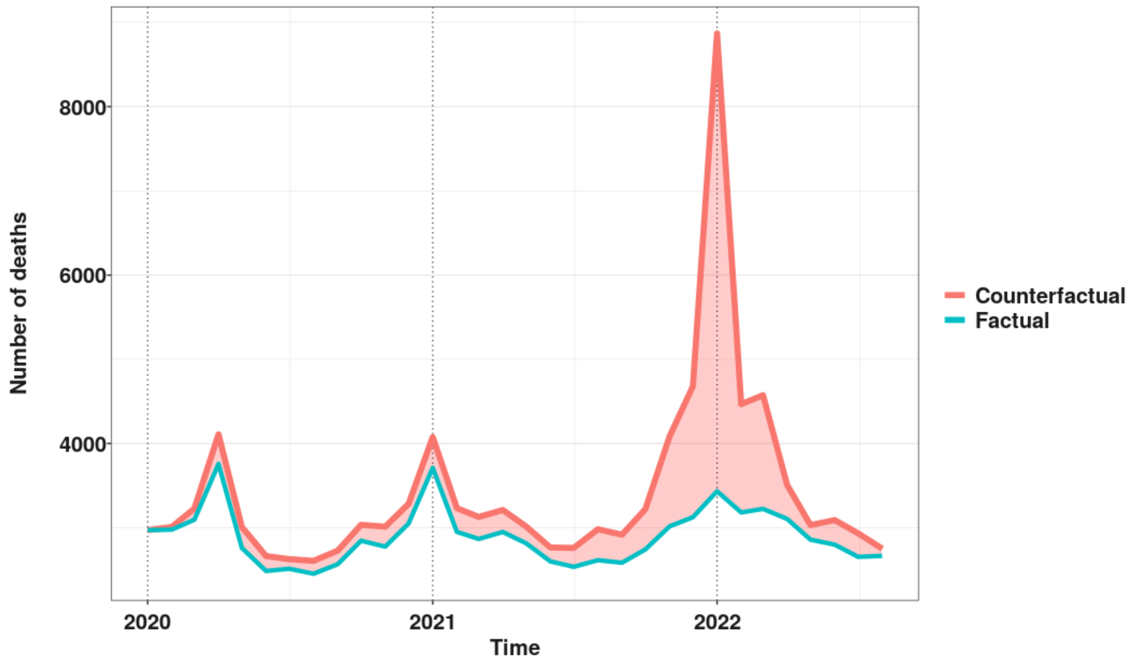


Figure 3.2: Comparison of the counterfactual number of deaths (red) against the observed number of deaths (blue) during 2020 to 2022 in Ireland.

$$cases_{t,k} \sim Poisson(10 \times x_{t,k}) \tag{3.5}$$

In Equation 3.5, $cases_{t,k}$ is the inferred number and $x_{t,k}$ is the reported number of cases at time t (only the first seven months of the year 2020) and county k. The model is implemented in R [259] using the JAGS software [221] and is run for $7,000$ iterations. The first 500 iterations are discarded as burn-in. The model is run for 4 chains and the convergence of the chains is checked using the R-hat diagnostic [37, 104], that were all close to the target value of 1, indicating good convergence.

3.3 Experimental Results

Overall, given the difficulty of the problem, we are very pleased with the outcomes of our experimental results. In this section, we now describe the three most important results of our work. Figure 3.1 compares the predicted outcomes from the implemented model to the actual number of cases of deaths. The vertical lines indicate the 95% posterior predictive credible intervals. The goodness of fit is measured using the $R^2 = 0.98$ criterion. Figure 3.1 demonstrates clearly that the model can successfully achieve the actual number of deaths in Ireland over the time period of study.

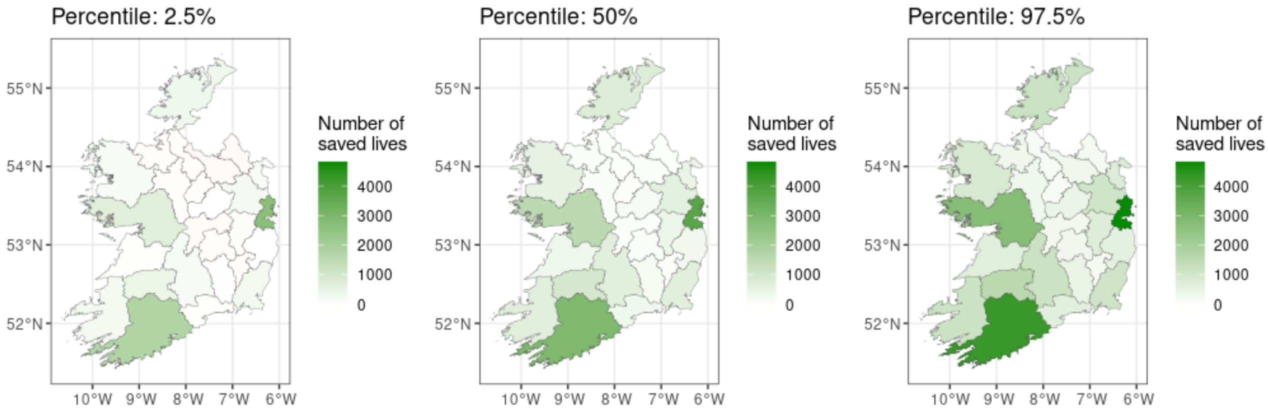


Figure 3.3: The number of lives saved because of lockdowns and vaccination in each county is depicted. From left to right, the maps are associated with 2.5%, 50% and 97.5% cumulative probability for the estimated numbers, respectively. The numbers in the 2.5% and the 97.5% maps indicate the 95% credible interval for saved lives in each county.

In order to estimate the number of lives saved by lockdowns and vaccinations we needed to generate counterfactual scenarios [60, 31]. This involves modifying a factual prior event and then assessing the consequences of the modification. We performed this by setting the SI and the vaccination rate to zero and then generating predictions for the number of deaths within this scenario. After this, we compared the counterfactual number of deaths with the actual number of deaths to estimate the number of lives saved with the availability of vaccination. Following this procedure, we estimated the number of lives saved by lockdowns and vaccinations in Ireland to be $16,876$ with a 95% credible interval of $[13,799 - 20,140]$. We illustrate the results in figure 3.2 by comparing the counterfactual number of deaths generated by our model with the actual number of deaths at the country level. The red line depicts the expected number of deaths under the counterfactual scenario whereas the blue line represents the actual number of deaths. The shaded area in red illustrates the difference between the values. This gap begins to widen after the first quarter of 2021. We believe that this is likely due to the successful rollout of vaccines in Ireland which began around this time. As shown in the figure 3.2, this gap reached its peak between September 2021 and May 2022 when around 2.5 times more deaths were observed under the counterfactual scenario. This peak gap can be explained by widespread vaccination among people in Ireland despite the absence of restrictive social distancing measures compared to those in place during 2020.

Finally, we considered the estimation of the number of deaths prevented in all of the counties of Ireland. As reported above, we consider the 26 counties in the Republic of Ireland. Figure 3.3 [a] illustrates the estimated number of deaths prevented in the counties of Ireland by lockdowns and vaccinations using three county-based maps. In figure 3.3 the maps from left to right indicate the 2.5%, 50% and 97.5% estimation percentiles respectively. Within the space available in this study, there are a few interesting observations to note.

The county of Dublin, shown in dark green across all three maps and characterized by the highest urban population, recorded the greatest number of lives saved. This was followed by Cork and Galway, which have the 2^{nd} and 3^{rd} largest populations in Ireland, respectively, with the majority of their residents living in rural areas. The fourth most populated county, Kildare, does not necessarily follow this pattern, its number of saved lives is not proportionate to its population rank, even though Kildare experienced both national and local lockdowns, unlike other counties that underwent only national restrictions. The lowest numbers of lives saved, shown in white in the middle panel, were observed in Cavan and Monaghan. This finding is particularly interesting, as both counties are predominantly rural. Unlike Cork and Galway, where rural populations also predominate but the number of lives saved was considerably higher, Cavan and Monaghan exhibited the lowest figures despite generally having fewer daily contacts. Multiple CSO-based summaries reported that Monaghan and Cavan were among the highest per-capita COVID-19 death rates nationally, early in the pandemic and also cumulatively. For example, RTÉ News [239] (using CSO data) noted Monaghan and Cavan had the highest death rates by February 2021, with Monaghan at 128.7 per 100,000 and Cavan at 118.1 per 100,000, despite their predominantly rural profiles. Later overviews in the Irish Independent [139] again listed Cavan and Monaghan among the highest cumulative COVID-19 death rates since the start of the pandemic, reinforcing that these counties fared worse than average on mortality outcomes. Taken together, these independent sources align with our counterfactual result that fewer lives were saved by lockdowns and vaccination in Cavan and Monaghan relative to counties like Galway or Cork: places that ultimately recorded higher mortality are exactly those where our model infers smaller intervention benefits. These county-level results and their interpretation could be further refined with additional socio-demographic and public health policy data, which are beyond the scope of the present study.

[a] The version of this map originally published in Pourshir Sefidi et al. [227] used a shapefile read via the now-retired `rgdal` package, which led to a subsequent misalignment between some county polygons and the correctly estimated posterior summaries. The figure reproduced here has been regenerated using another R spatial package (sf) to ensure that polygons and numerical results are correctly aligned. The underlying Bayesian model estimates and numerical results reported in the paper were unaffected and remain valid; this corrected map in the thesis should be regarded as the authoritative graphical representation.

3.4 Conclusions and Discussion

In this study, we have developed a Bayesian hierarchical Poisson regression model to estimate the number of lives saved by lockdowns and vaccinations in Ireland during the years 2020 to 2022. Overall our model, as described in section 3.2, was able to successfully retrieve the actual number of deaths in Ireland during the period of study. Using the model we estimated that on average $16,876$ (95% CI: $13,799-20,140$) lives were saved by lockdowns and vaccinations in Ireland. We also showed (for example in figure 3.2) that the number of saved lives peaked between September 2021 and May 2022 where an estimated 2.5 times more deaths were prevented as a result of widespread vaccination among the population in Ireland. This happened despite the absence of restrictive physical distancing measures compared to 2020. For county-specific analysis, we showed in figure 3.3 that Dublin county had the most significant number of saved lives with Cork and Galway following closely behind.

We believe the BHPR approach we used in this study has the potential to be used in similar problem settings where data is nested in multiple levels and there is uncertainty about some of the observed values in the predictors. For example, we showed how to account for the uncertainty in the number of confirmed cases by putting a prior distribution on the suspicious values using the Bayesian framework. In this work, we did not focus on the variations of the effects in different counties and the reasons behind them. Many factors such as population density, demographics and socio-economic variables could possibly explain the variations. Indeed, during summer 2020 one county (Kildare) experienced a county-level lockdown while its neighbouring counties (Laois, Offaly and Dublin) were not subject to such a lockdown [262]. Situations like this mean that further considerations are required for future work which can interpret our results in a broader context.

4

Long-Term Health Consequences: COVID-19 and Cardiovascular Disease

Publication and Author Contributions

This chapter is based on the published article:

> Pourshir Sefidi, N., Mooney, P., An exploration of the connection between COVID-19 and cardiovascular disease (CVD) in European countries. *Journal of Public Health*, pp.1-11, (2024). `https://doi.org/10.1007/s10389-024-02372-2`

This study was conducted collaboratively; however, I led all major aspects of the research. I defined the research scope, applied for and obtained permission to access the *Survey of Health, Ageing and Retirement in Europe* (SHARE) data, and curated and preprocessed the dataset for analysis. I developed and implemented the Bayesian Hierarchical Logistic Regression (BHLR) model, carried out all statistical analyses, interpreted the results, and prepared the manuscript. My co-authors provided supervisory input, methodological advice, and editorial feedback. The content presented in this chapter is consistent with the published paper, with minor stylistic adjustments for coherence within the thesis.

Summary of Key Contributions

- Investigated the association between COVID-19 infection and cardiovascular disease (CVD) at the macro, country level across 26 European countries.
- Developed a Bayesian Hierarchical Logistic Regression (BHLR) model to estimate the impact of COVID-19 on CVD risk while accounting for between-country heterogeneity and spatial variation.

- Analysed data from the Survey of Health, Ageing and Retirement in Europe (SHARE), focusing on individuals aged 50 and above.
- Estimated that COVID-19 infection increases the odds of developing CVD by approximately 20% (95% CI: 1–44%), with substantial heterogeneity across European regions.
- Identified hypertension, diabetes, chronic lung disease, and elevated BMI as key risk factors that further exacerbate post-COVID cardiovascular risk.
- Highlighted geographic variation in COVID-19's cardiovascular impact, with certain countries, such as the Czech Republic, exhibiting a higher probability of increased complications.
- Provided data-driven insights to inform public health policy, emphasizing the importance of long-term cardiovascular monitoring and prevention strategies in the post-pandemic era.

4.1 Introduction

The COVID-19 pandemic, a worldwide outbreak of the coronavirus disease starting in 2019 and caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has led to an increase in global mortality rates in recent years [295]. According to the World Health Organization (WHO), Europe had recorded over 62 million confirmed cases of COVID-19 and approximately 1 million deaths by the end of August 2021, and the virus continues to spread to this day [300]. Clinical manifestations of COVID-19 can range from asymptomatic or mild respiratory symptoms to severe conditions such as bilateral pneumonia, respiratory failure, and cardiac failure [6, 47]. While the majority (81%) of COVID-19 cases in the initial two years of the pandemic were categorized as mild, approximately 14% were severe, necessitating hospitalization. Additionally, 5% of the cases were critical, marked by evident airway failure, septic shock, and/or multi-organ dysfunction or failure, demanding intensive care [303]. Individuals with compromised immune systems are generally more susceptible to COVID-19 infection. Older adults with underlying health conditions face an elevated risk of experiencing severe outcomes from the disease [59, 116, 133, 248]. The majority of young people and children typically experience only mild symptoms or remain asymptomatic [116].

On the other hand, cardiovascular disease (CVD) is the primary reason for death and a significant source of illness in Europe [263]. Effectively addressing CVD and its associated risk factors is not only helpful in preventing future incidents like myocardial infarction (heart attack), stroke, and CVD-related mortalities [18], but also contributes to the overall improvement of public health and the quality of life for individuals across Europe. Focusing on preventive strategies and managing risk factors improves healthcare outcomes by refining public health policies and mitigating the long-term cardiac implications of COVID-19 infection. Such an approach not only lessens the demand for healthcare resources but also reduces the economic pressures linked to treating advanced CVD. Moreover, efficient management of CVD risk factors contributes to a healthier workforce, which is essential for communities' economic stability and growth.

4.1.1 Related Literature

Approximately 3.9 million deaths occur annually in Europe from CVD, constituting 45% of all recorded deaths [170]. However, there is significant variation in the rates of cardiovascular morbidity and mortality across various European countries [93, 158, 192, 269]. These differences can be ascribed to variations in racial/ethnic composition, prevalence of underlying conditions (e.g., diabetes, obesity, hypertension etc.), healthcare accessibility, socio-economic and demographic factors, regional lifestyle distinctions, and a range of other influencing factors [145].

Numerous reports have documented that people infected with SARS-CoV-2 experience a range of cardiac issues and cardiovascular complications which include myocardial and cardiac function impairment, as well as conditions such as myocarditis, pericarditis, arrhythmias, acute myocardial infarction, stroke, thromboembolism, ischaemic heart disease, and sudden cardiac death [117, 118, 143, 246, 304]. Recently, there has been a growing body of literature on the possible lasting cardiovascular sequelae of COVID-19. Puntmann et al. [231] studied a German single-centre cohort involving 346 individuals with previous COVID-19 infection. This study revealed that 53% of the patients continued to experience persistent cardiac symptoms, even after an average follow-up duration of 329 days following their initial infection. Additionally, 5% of the participants reported the development of new symptoms during this follow-up period. In a separate study, Xie et al. [304] examined a group of 153,760 individuals who had recovered from COVID-19 using data from the U.S. Department of Veterans Affairs. An increased risk of various cardiovascular outcomes was observed 12 months after the initial infection. A UK study identified an increase in cardiovascular diagnoses, including a six-fold rise in atrial arrhythmias and a five-fold increase in venous thromboses following COVID-19 [237]. However, in this study, the risk of cardiovascular disorders returned to baseline levels within one-year post-acute infection. Similarly, Katsoularis et al. [143] analyzed a cohort of 86,742 individuals who had contracted COVID-19 in Sweden. The findings indicated that the risk of cardiovascular events for both myocardial infarction and ischemic stroke was significantly elevated in the initial weeks post-infection. In a separate study conducted by Knight et al. [150], the authors examined the health outcomes of 48 million adults in England and Wales, including 125,985 hospitalized and 1,319,789 non-hospitalized individuals within 28 days of a COVID-19 diagnosis. The researchers noted that while the relative incidence of vascular events decreases following a COVID-19 diagnosis, the risk remains heightened for a significant duration, extending up to 49 weeks, for both arterial and venous complications. Furthermore, Ayoubkhani et al. [11] extended the observations made on a dataset from 47,780 hospitalized individuals with COVID-19 in England. Their study revealed a higher occurrence of both new-onset diabetes and major adverse cardiac events in individuals in the recovery phase from COVID-19. A study conducted in Spain involving 587 individuals who had recovered from COVID-19 infection found that at a one-year follow-up, 2% of these patients had developed new-onset hypertension and new cases of heart failure. The authors also noted that 2.7% of these patients experienced the onset of right-sided heart failure without any prior hypertension or left heart failure [171]. Huang et al. [134] showed a significant increase in mortality rate during the year following the infection by studying 2,469 Chinese patients with COVID-19. This increase was often associated with sudden cardiac deaths triggered by arrhythmias or thrombotic events. Likewise, Ruan et al. [240] documented that among 68 patients who died of

COVID-19, myocardial dysfunction played an important role, either as the sole cause or as a contributing factor, in 40% of the cases.

4.1.2 Contributions of this Research

As mentioned above in Section 4.1.1, numerous research studies have explored the connection between COVID-19 and CVD in individuals who have been infected or recovered from the virus. These studies have primarily investigated the cardiovascular impact of COVID-19 by assessing the prevalence of clinical characteristics and symptoms associated with CVD, with a particular focus on cardiac injury, as indicated by elevated cardiac troponin levels [280, 305, 304]. Elevated cardiac troponin levels increase sharply within three to 12 hours after a heart attack and peak about 24 hours after a heart attack. The scope of such evidence is further limited by its reliance on data from single centres or single countries, its bias towards certain groups (e.g., white men), and its exclusive focus on either severely hospitalized COVID-19 patients or individuals with pre-existing myocardial conditions related to underlying CVD.

The work described here aims to complement prior research, which primarily focused on the effect of COVID-19 infection on the risk of CVD at a micro level, by investigating this effect at a macro, country level in Europe. We believe this is an area of critical importance given the ongoing presence of COVID-19 and its expected persistence in the coming years [51, 297, 300], despite a decrease in mortality rates compared to the pandemic's early stages [260]. Our study's relevance is strengthened by highlighting the virus's detrimental effects on heart health. Even as societies return to normalcy, the potential for COVID-19 to precipitate cardiovascular issues continues to be a significant concern. This is crucial for two reasons; firstly, the persistence of COVID-19, alongside its capacity to impair heart health, underscores the ongoing need for public health strategies that address the impacts of the virus. Secondly, the recent increase in heart attack fatalities across all age groups [215, 243], potentially linked to post-COVID conditions [208, 131], further justifies the significance of our research.

Our work delivers novelty and impact from our comprehensive analysis of survey data from individuals over 50 years of age, both male and female, across 26 European countries, identified as having a heightened susceptibility to severe COVID-19 infections and an increased likelihood of mortality related to the virus due to their age [112, 116, 133, 194]. The importance of focusing on this demographic cannot be overstated, especially considering Europe's trend toward an ageing population [88, 258, 209]. We also provide an estimation of the extent to which COVID-19 infection, along with other risk factors such as hypertension, diabetes, chronic lung disease, and being overweight (all of which have been shown to increase the risk of experiencing heart problems [177, 281]) actually exacerbated the risk of developing CVD during the first 17 months of the pandemic.

In our work, we utilized a Bayesian Hierarchical Logistic Regression (BHLR) model to incorporate country-level effects as well as continent-level effects. This model enables us to account for spatial variations and estimate the overall effect at the continental level. By implementing a hierarchical modelling approach, our analysis benefits from partial information pooling, a process that facilitates the sharing of data across various levels to enhance parameter estimation [105]. Within the scope of our study, this procedure allows the aggregation of data from multiple countries, leading to more precise and reliable estimates.

Our findings indicate that in many European countries, COVID-19 infections have increased the odds of developing new CVD, although the extent of this increase differs from country to country. Also, at the continental level, we found strong evidence that COVID-19 has heightened the risk of CVD incidence overall in Europe. Furthermore, our analysis corroborates the conclusions drawn from prior research (such as Bays et al. [21], Beckerman [24], Ramalho and Shah [235], Wang [281], Xu et al. [305]), which suggest that risk factors, including hypertension, diabetes, and chronic lung disease, significantly elevate the odds of developing CVD. Healthcare professionals, policymakers, and researchers in the field will find our insights invaluable for forming future health interventions, formulating policies, and devising strategies aimed at strengthening the healthcare system and enhancing economic resilience against pandemics.

The remainder of this chapter is structured as follows. In section 4.2, we describe the data used in our research, highlighting its constraints. In section 4.3, we explain our modelling framework. Our findings from the experimental analysis are summarised and discussed in section 4.4. Finally, we summarise the chapter in section 4.5, by considering the limitations of our study and potential areas for future research.

4.2 Data Description

This study is based on data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a comprehensive longitudinal database containing micro-data related to health, socio-economic status, and inter-generational transfers for individuals aged 50 and above in 26 European countries [34]. We utilized data from Wave 8 of SHARE, collected from October 2019 to December 2020, alongside data from two rounds of the SHARE Corona Survey (SCS) carried out in the summers of 2020 and 2021 [32, 33], which also covered 26 European countries. More detailed information on the countries included in the study is provided in Table 4.1. The SCS1 and SCS2 questionnaires addressed critical aspects of life and included specific inquiries about COVID-19 infections and changes in health and life circumstances both before and after the COVID-19 pandemic. To investigate the

Table 4.1: Summary of demographic and health characteristics from SHARE Corona Surveys (SCS)

	SHARE Corona Surveys (SCS1 & SCS2)	
	N	%
COVID-19 contagion	1,811	6.55
Gender		
Male	11,090	40.16
Female	16,523	59.83
Body mass index (BMI)		
BMI $\leq$ 25	9,301	33.68
25 $<$ BMI $\leq$ 30	11,213	40.60
30 $<$ BMI	6,381	23.10
Comorbidity		
Hypertension	13,502	48.89
Diabetes	4,340	15.71
Chronic lung disease	1,743	6.31
Country		
Austria	1,023	3.70
Belgium	1,395	5.05
Bulgaria	464	1.68
Croatia	925	3.34
Cyprus	266	0.96
Czech Republic	1,474	5.33
Denmark	1,108	4.01
Estonia	2,069	7.49
Finland	787	2.85
France	1,374	4.97
Germany	1,580	5.72
Greece	2,268	8.21
Hungary	386	1.39
Italy	1,617	5.85
Latvia	540	1.95
Lithuania	845	3.06
Luxembourg	626	2.26
Malta	572	2.07
Netherlands	424	1.53
Poland	1,282	4.64
Romania	977	3.53
Slovakia	814	2.94
Slovenia	1,735	6.28
Spain	848	3.07
Sweden	764	2.76
Switzerland	1,450	5.25

effect of COVID-19 infection on the incidence of CVD, we only considered individuals with no prior history of CVD before the pandemic in our study. Among the 45,797 European participants in the regular SHARE Wave 8 survey (October 2019 to the end of 2020), 39,735 (or 87%) individuals reported no history of heart-related issues, including heart attack, myocardial infarction, coronary thrombosis, or congestive heart failure. Of these, it was possible to match 27,496 participants (69%) who also took part in both SCS1 and SCS2. In this research, we only used data from individuals who met the initial SHARE sample criteria. This required individuals to be 50 years of age or older, resulting in the removal of 108 observations. Additionally, we refined our analytical sample by excluding individuals with missing data on covariates of interest, such as weight, height, diabetes, hypertension, chronic lung disease, and heart issues. This led to the omitting of a further 718 observations. Consequently, the final analytical sample consisted of 26,895 respondents. Table 4.1 provides more descriptive information on this sample.

4.2.1 Variables Used: Independent Variables

For this study, we considered country, age, gender, body mass index (BMI) — calculated by dividing an adult's weight in kilograms by their height in meters squared, COVID-19 infection, diabetes, hypertension, and chronic lung disease statuses as our independent variables. Within SHARE the interviewers were responsible for recording the respondent's gender through observation (and asking if unsure) and noting the country where the interview was conducted. Additionally, respondents were queried with the following set of questions. The general release guide for the questionnaires is available in the Survey of Health, Ageing and Retirement in Europe [257].

Question 1: In which year were you born?

Question 2: Approximately how much do you weigh?

Question 3: How tall are you?

Question 4: Have you tested positive for the coronavirus?

Question 5: Do you have diabetes or high blood sugar?

Question 6: Do you have high blood pressure or hypertension?

Question 7: Do you have chronic lung disease such as chronic bronchitis or emphysema?

Respondents were required to provide numeric answers for questions 1, 2, and 3, while they had the choice to respond with either "Yes" or "No" in questions 4 to 7. In this survey, a “Yes” response signified a positive COVID-19 test result or a doctor-diagnosed illness. Conversely, if the test result was negative or no doctor-diagnosed illness was reported, the answer was recorded as “No”. In addition to these options, respondents could also select “Refusal”, “Don’t know”, or “Not applicable” if they either chose not to answer, were unsure, or if the question did not apply to them. All such responses (“Refusal”, “Don’t know”, and “Not applicable”) were treated as missing values in our analysis.

4.2.2 Variable Used: Dependent Variable

Given our focus on understanding the impact of COVID-19 infection on cardiovascular health, our dependent variable was determined by the question: “*Did you have a heart attack including myocardial infarction or coronary thrombosis or any other heart problem including congestive heart failure, which a doctor diagnosed, and are you either currently being treated for, or bothered by it since October 2019?*” Here, a response of “Yes” indicates that one of the aforementioned conditions was diagnosed by a doctor, while a response of “No” signifies that none of these conditions was doctor-diagnosed. Additionally, any responses of “Refusal”, “Don’t know”, or “Not applicable” were treated as missing values.

4.3 BHLR Modelling Procedure

In this section, we explain the modelling framework we used to build the BHLR model, whereby y_i represents whether an individual has or does not have CVD, with i ranging from 1 to 26,570. We write the model hierarchically as follows:

$$y_i \sim Bernoulli(P_i) \tag{4.1}$$

where P_i represents the probability of an individual i being affected by CVD. This is modelled as:

$$\begin{aligned} logit(P_i) = \alpha_c &+ \beta_c^{gender} \times gender_i + \beta_c^{age} \times age_i + \beta_c^{BMI} \times BMI_i \\ &+ \beta_c^{hypertension} \times hypertension_i + \beta_c^{diabetes} \times diabetes_i \\ &+ \beta_c^{lung\ disease} \times lung\ disease_i + \beta_c^{covid} \times covid_i \end{aligned} \tag{4.2}$$

In this model:

- α_c represents the intercept at the country level.
- β_c^{gender}, β_c^{age}, β_c^{BMI}, $\beta_c^{hypertension}$, $\beta_c^{diabetes}$, and $\beta_c^{lung\ disease}$ denote the country-level effects of gender, age, BMI, hypertension, diabetes, and lung disease respectively.
- β_c^{covid} signifies the country-level effect of being diagnosed with COVID-19.

We then add the continent-level effects into the model, structuring them as hierarchical priors on the effects at the country level as follows in Equation 4.3. To simplify, we represent the j^{th} effect in the country c as β_c^j.

$$\beta_c^j \sim Normal(\mu^j, \sigma^j) \tag{4.3}$$

where μ^j denotes the continent-level effect (i.e. Europe's average effect) of covariate j, and σ^j indicates the continent-level standard deviation of the effect of covariate j. Below, we show the non-informative hyperpriors used:

$$\begin{aligned} \mu^j &\sim Normal(0, 10) \\ \sigma^j &\sim StudentT(0, 1, 1)^+ \end{aligned} \tag{4.4}$$

where $StudentT(0, 1, 1)^+$ refers to a Student's t-distribution [286] truncated to positive values.

4.4 Results and Discussion

Despite COVID-19 no longer being classified as a global health emergency [212], its lasting health issues, especially on heart health, continue to be a reason for concern. As the COVID-19 pandemic extends into its fifth year, as defined by the lead COVID official at the WHO [19, 65, 132], the need for ongoing attention and research into its long-term impact on cardiovascular health is still crucial [184]. With CVD as a major health challenge in Europe [252, 263], understanding the extent to which COVID-19 exacerbates heart problems, especially in conjunction with underlying conditions like diabetes, being overweight (BMI $\geq$ 25), hypertension, and chronic respiratory disease is very important.

4.4.1 Impact of COVID-19 Infection and Risk Factors for Cardio-vascular Health

Our analysis of SHARE survey data, including 26,895 individuals over 50 years of age from 26 European countries, adjusted for gender and age, evaluates the impact of COVID-19 infection and other risk factors on cardiovascular health as reflected by changes in the odds of CVD. The results, as depicted in Figure 4.1, provide insights into the effects with corresponding 95% and 80% credible intervals (CI). The results suggest that COVID-19 infection in Europe is associated with, on average, a 20% increase (95% CI: 1–44%) in the odds of developing CVD. Furthermore, among the risk factors for CVD, our model's findings place hypertension in a position of particular importance. The analysis reveals that hypertension is associated with a significant increase of 140% (95% CI: 117–163%) in the odds of CVD. This result is well aligned with the findings of prior research, including studies conducted by Mills et al. [187] and Pranata et al. [229].

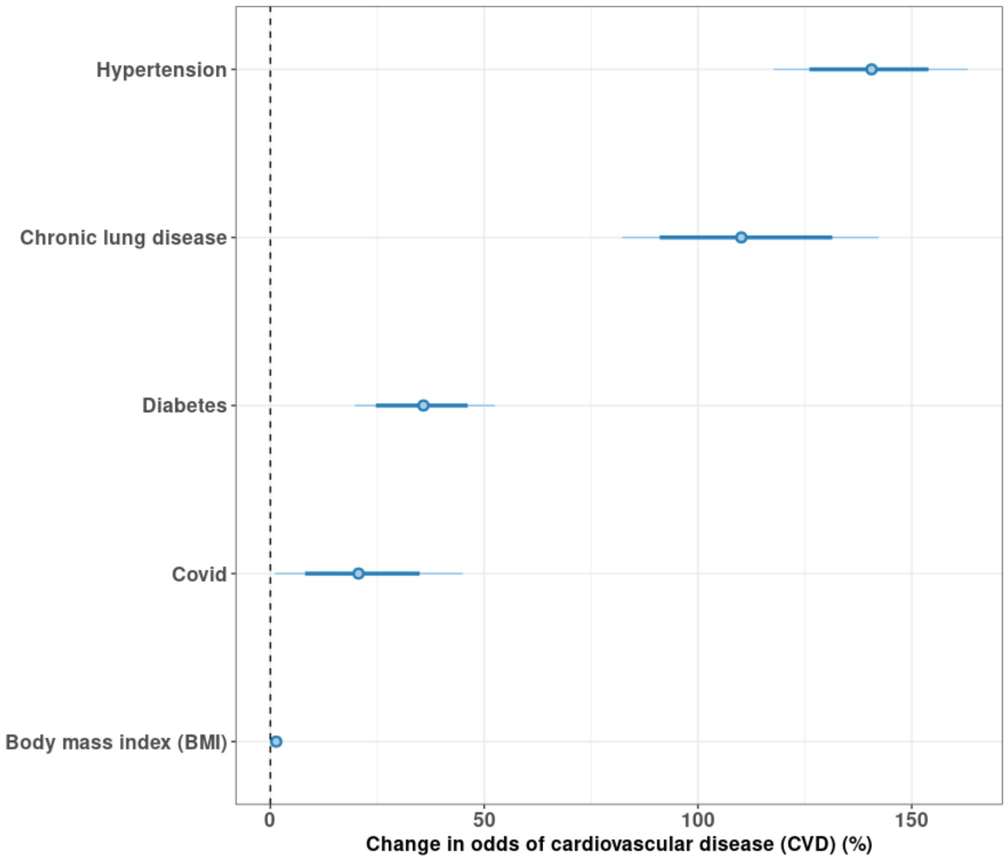


Figure 4.1: Association of various underlying conditions with CVD. The 95% credible intervals are indicated in light blue, while the 80% credible intervals are highlighted by the dark blue bars.

Although chronic lung disease is not consistently highlighted as one of the primary risk factors for CVD across various sources [21, 24, 142, 177, 264] — with other aspects often showing a higher impact — our findings suggest that chronic lung disease is associated with a 110% (95% CI: 82–142%) increase in the risk of CVD. This result indicates that while chronic lung disease may not have always been at the forefront of traditional risk profiles, its role in exacerbating cardiovascular risk should not be overlooked.

Diabetes emerges as another risk factor for cardiovascular disease, closely following chronic lung disease in its association with an increased risk of developing CVD. Our analysis indicates that diabetes is linked to a 35% (95% CI: 20–52%) increase in the odds of developing CVD. Hence, the well-established link between diabetes and CVD [98, 224, 238, 292] is also emphasized in our study.

Finally, our results indicate that BMI has a positive association with an increase in the incidence rate of developing CVD. This is demonstrated by a 1% (95% CI: 0.4–2%) increase in the odds of CVD for every unit increase in BMI. Please note that BMI is a continuous variable, unlike other risk factors. Its smaller association should not be underestimated when compared to other risk factors, as it is reported in terms of per unit increase in BMI.

In summary, our findings underline the association of COVID-19 infection, hypertension, chronic lung disease, diabetes, and elevated BMI with the risk of developing CVD. The implications of these findings are important for public health policymakers and clinical practice across Europe. This research advocates for a holistic approach to CVD prevention that integrates the management of COVID-19 alongside traditional cardiovascular risk factors.

Furthermore, we suggest the need for ongoing surveillance and study of the long-term impacts of COVID-19 on cardiovascular health. By adopting such evidence-based, multifaceted strategies, it is possible to reduce the cardiovascular disease burden and improve overall public health outcomes across the continent, ensuring a healthier future for Europe's ageing population.

4.4.2 Geographical Variations in the COVID-19 Effect

To investigate whether the effects of COVID-19 infection on the odds of having CVD vary across different European countries, we calculated the probability of the country-level effects of COVID-19 being greater than the continent-level effect of COVID-19 (also known as Europe's average effect) as the reference. This is denoted as $P(\beta_c^{covid} > \mu^{covid})$, for each country c in the list of countries. Figure 4.2 shows the results of this analysis depicted on the map of Europe, excluding countries that are absent from our study. According to the map, this probability ranges between 28% and 70%, with the Czech Republic having a 70% probability and Estonia having a 28% probability of experiencing a higher effect than Europe's average effect. The probabilities for most countries fall between 40%–60%, meaning that we cannot tell with great certainty whether the effect in these countries has been either below or above the average. In other words, there is a low chance that the effects of COVID-19 vary significantly across these countries. However, Estonia, with a 72% probability of experiencing a lower effect than average, and the Czech Republic, with a 70% probability of experiencing a higher effect than average, deserve further research attention due to these relatively high probabilities. Further investigation is required in order to determine the cause of this disparity.

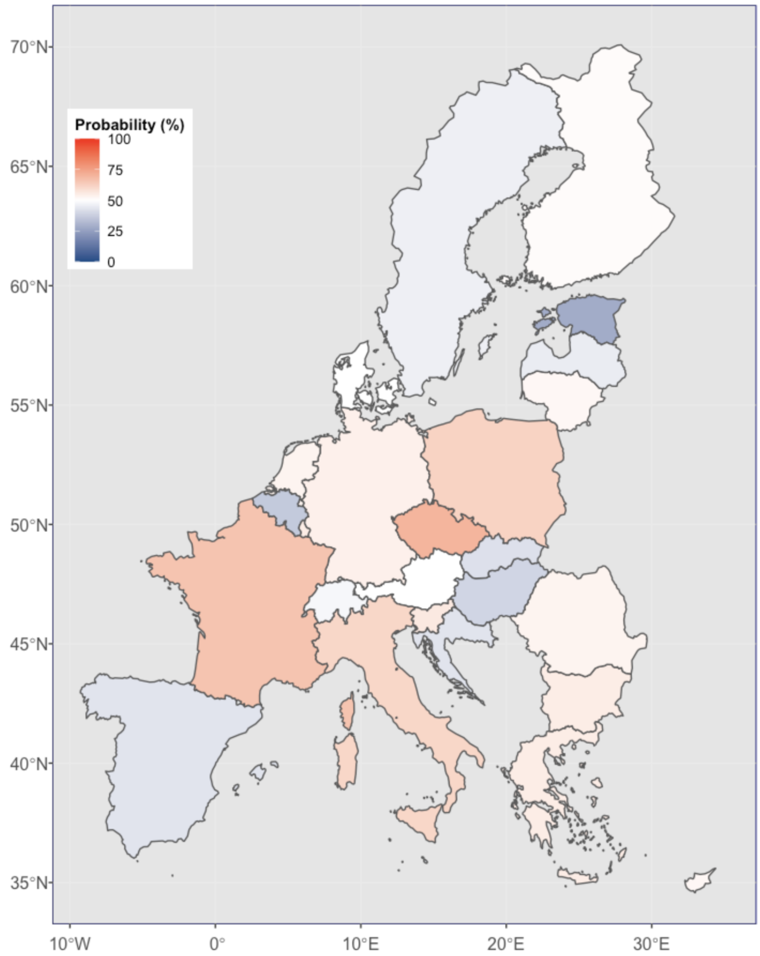


Figure 4.2: Probability of COVID-19's effect being greater than that of Europe's average.

One possible explanation for this variation could be the influence of disparities in public health measures and the robustness of the corresponding healthcare systems [90, 169]. In the context of Estonia and the Czech Republic, differences in their COVID-19 pandemic management, such as different approaches to vaccination rollout and the timing of implementing or lifting lockdown measures, highlight this point. The Czech Republic encountered numerous obstacles during its vaccine deployment, notable for its belated commencement and one of the slowest distribution rates across Europe [152]. These challenges were further exacerbated by logistical issues, such as an online registration system failure and a lack of essential supplies like syringes and needles, significantly impeding vaccination efforts [152]. On the other hand, Estonia, known for its advanced digital infrastructure, leveraged this to enhance its pandemic response [265], possibly influencing a more streamlined vaccination process. Moreover, the Czech Republic's decision to relax lockdown restrictions ahead of the holiday season, without accounting for the advent of more transmissible virus strains, precipitated a sharp increase in case numbers [152].

In addition, individual risk factors such as genetics, lifestyle choices such as smoking [92, 272] and alcohol consumption [138], and psychological factors such as depression [8, 91] and anxiety [101] could contribute to this variability. Furthermore, the data collection process during the pandemic faced considerable challenges. In the early stages, there was a notable lack of widespread testing which introduced significant uncertainty regarding the true number of positive cases [4, 184, 227, 234]. To maintain data integrity, we excluded all respondents who reported "I don't know" or "Not applicable" about the status of their COVID-19 infection. This exclusion inevitably resulted in a smaller dataset and consequently amplified the uncertainty, especially for country-specific parameters, associated with our results.

Moreover, the sample sizes of infected individuals in each country may have not been large enough to provide a robust estimate of the virus's impact on heart health. On the other hand, the reliability of COVID-19 testing itself was a concern. The probability of receiving a false negative was higher than that of a false positive [289], which could have led to an underestimation of the virus's prevalence and its subsequent cardiovascular effects. Such diagnostic inaccuracies would affect the accuracy of the estimated odds ratio of CVD post-COVID infection. This, in turn, could obscure the true extent of the pandemic's impact on cardiovascular health. Indeed this could suggest that the actual situation may be more severe than indicated by the data.

4.5 Conclusions and Future Work

This study analyzed the effects of COVID-19 on the cardiovascular health of individuals aged 50 and over in 26 European countries, based on the SHARE survey data. The results of our study indicate a 20% average rise in CVD risk post-COVID-19 infection, while controlling for risk factors including hypertension, diabetes, chronic lung disease, and elevated BMI. Among all the risk factors, hypertension stands out at the top, presenting an 140% heightened risk for CVD, while chronic lung disease also significantly raises the risk by 110%, followed by diabetes, which accounts for a 35% increase in risk. We believe that this is a serious situation, necessitating a reassessment of health policies and clinical approaches within these countries. Indeed, these results indicate essential intervention points for the demographic of individuals aged over 50 throughout all of Europe.

Our research not only contributes to the growing body of evidence on the long-term health consequences of COVID-19, but also offers a comprehensive overview of the interplay between the virus and cardiovascular health risks. Our spatial analysis provides further insight into the variability of COVID-19's impact across different European countries relative to the overall continental effect. The Czech Republic is likely to encounter a more severe impact, with a 70% probability of higher CVD complications from COVID-19 compared to the European mean, with France close behind at a 66% probability. At the other end of the spectrum, Estonia shows only a 28% probability of being impacted more than the average for Europe.

There are some interesting and timely opportunities for continuing and future work. We believe that future studies should focus on implementing a longitudinal follow-up using Wave 9 of the SHARE dataset, scheduled to be completed by 2024. This would allow for a detailed examination of the long-term impact of COVID-19 infection on cardiovascular health, marking almost five years since the onset of the pandemic. Such research will be the first of its kind to explore the effects of the COVID-19 virus on heart health over such an extended period of time. Future work in this respect can also take into account the evolution of the virus by considering the mutation timeline in order to provide a more detailed understanding of the infection's long-term impact on heart health. Moreover, it is crucial to investigate the impact of lifestyle and behavioural shifts caused by the pandemic, including changes to people's physical activity [255], dietary patterns [113], and levels of stress and depression [210] on cardiovascular health outcomes.

Additionally, as vaccination programs continue to expand, studying how immunization and the frequency of vaccinations influence CVD risk among individuals with previous COVID-19 infections has the potential to provide novel insights. Given the anticipation that these aspects will be covered in the forthcoming SHARE wave questionnaire, such research could significantly contribute to designing targeted lifestyle interventions aimed at reducing CVD risk.

Finally, another critical avenue for future research could involve an assessment of the pandemic's toll on national healthcare systems, in particular when viewed through the lens of deferred or cancelled specialist appointments. Investigating how these disruptions have influenced cardiovascular health across populations could yield valuable insights for enhancing future pandemic preparedness and shaping national healthcare policy. Such research could highlight the need for resilient healthcare frameworks capable of sustaining continuous care, even in the face of global health crises, thereby ensuring that cardiovascular care remains a priority to mitigate long-term health repercussions.

5

Crime Trends During the COVID-19 Pandemic

Publication and Author Contributions

This chapter is based on the published article:

> Pourshir Sefidi, N., Shoari Nejad, A., Mooney, P., Effects of Pandemic Response Measures on Crime Counts in English and Welsh Local Authorities. *Journal of Applied Spatial Analysis and Policy*, 18(1), p.15, (2025). `https://doi.org/10.1007/s12061-024-09614-6`

This study was conducted collaboratively; however, I led all major aspects of the research. I identified the research problem, collected and preprocessed the publicly available crime and lockdown stringency data, developed and implemented the Bayesian spatiotemporal model, carried out all statistical analyses and visualisations, interpreted the findings, and wrote the manuscript. My co-authors contributed through supervisory guidance, theoretical discussion, and editorial feedback. The content presented in this chapter is consistent with the published paper, with minor formatting adjustments for coherence within the thesis.

Summary of Key Contributions

- Conducted a comprehensive spatiotemporal analysis of crime patterns in England and Wales over a nine-year period (2015–2023), covering pre-pandemic, pandemic, and post-pandemic phases.
- Investigated the impact of COVID-19 lockdown measures on different types of crime, using the Oxford COVID-19 Stringency Index as a proxy for restriction intensity.
- Developed a Bayesian spatiotemporal model to estimate the effect of restriction policies on crime across local authorities while accounting for spatial dependencies and temporal trends.

- Identified that while some crime categories (e.g., burglary, vehicle crime, and robbery) have remained below pre-pandemic levels, others (e.g., shoplifting, drug offences, and public order incidents) have returned to or exceeded pre-pandemic trends.

- Provided empirical evidence of spatial heterogeneity in crime responses, showing that restriction policies had differing effects across local authorities.

- Interpreted findings through established criminological frameworks such as Routine Activities Theory (RAT), General Strain Theory (GST), and Situational Action Theory (SAT), linking observed crime shifts to underlying behavioural mechanisms.

- Offered data-driven policy recommendations for law enforcement and policymakers to strengthen crime prevention and community safety strategies during future public health crises.

5.1 Introduction

During the COVID-19 pandemic, restrictions on the movement of citizens were enacted in almost every country worldwide to control the spread of the virus. The UK Government was no exception, implementing a series of extended measures in England and Wales beginning in March 2020. These lockdown-style policies have profoundly affected various sectors, including physical and mental health [230, 173, 211], economic performance [144], social interactions [137, 42], mobility [85], and more. Recent studies underscore the significant impact of the pandemic and associated lockdowns on different types of crime globally [122, 155, 58, 50, 80]. Investigating crime is a complex and multi-dimensional problem. Examining crime in relation to its spatial and temporal attributes helps researchers identify patterns, potentially illuminating the causes or influences behind crime in specific areas. This information is invaluable for shaping crime management policies within distinct regions and timeframes [62]. As we approach the three-year mark since the beginning of the COVID-19 pandemic, it is clear that lockdown-style policies have significantly altered people's daily routines, leading to discernible shifts in crime patterns.

While there is abundant research on the effects of government policies during the COVID-19 pandemic on crime [201, 109, 129], studies exploring the enduring post-pandemic effects and varied regional responses within England and Wales are scarce. This research aims to address this gap by analyzing the association between pandemic measures and crime counts in the local authorities of both England and Wales. Prior studies [155, 156, 199, 94, 82, 256, 163, 97, 271] have explored UK crime patterns, these were mostly confined to the national level or focused solely on selected cities. Our study broadens this scope to encompass all local authorities. This expansion is important since trends at the national level could be predominantly driven by data from a few outlier regions. Additionally, studying crime at the local authority level offers a well-balanced and strategic perspective that bridges the gap between broader national analysis and highly specific street-level or neighbourhood data. At the local authority scale, it becomes possible to identify patterns and trends that are representative of larger and more diverse communities and encompass various environments and demographics. This level of analysis helps us avoid the potential interference and fluctuations that can obscure meaningful trends in extremely detailed analyses where day-to-day variations might overshadow significant patterns. Furthermore, local authorities typically bear the responsibility of resource allocation and policy agenda-setting for their entire jurisdiction. By examining crime at this level, decision-makers are in a better position to allocate resources, establish priorities, and develop strategies with a broad impact. In essence, while national level and more fine-grained analysis has great value, the local authority level provides an ideal framework for gaining a holistic understanding around implementing strategic measures in crime prevention and response. Consequently, this study focuses on three main research questions:

- **RQ1:** How have different crime types' patterns evolved over time in the local authorities of England and Wales and have these patterns been influenced by the pandemic and its restrictions?
- **RQ2:** If there were changes in crime patterns during the pandemic, have these changes persisted post-pandemic?
- **RQ3:** What is the magnitude of the effect of restriction policies on the number of crimes within the local authorities for each crime type?

To address RQ1 we employ heatmaps to illustrate crime patterns over nine years, encompassing periods before, during, and after the pandemic. These heatmaps will assist in determining whether these trends are also evident in smaller, less populated regions. For RQ2, we reference the latest data from the UK police to assess whether different types of crime have returned to their pre-pandemic levels. Lastly, for RQ3, we construct a spatio-temporal regression model to estimate the effects of restriction intensity. We used the Stringency Index [121] as a proxy measure for restriction intensity in different local authorities.

The structure of the remainder of our research is outlined as follows: in section 5.2, we look at some of the most relevant literature pertaining to this domain. Section 5.3 outlines upon our data management approach, highlighting its limitations and the methodology adopted for this study. Our findings from the experimental analysis are summarised and discussed in section 5.4. Lastly, the chapter closes with section 5.5 where the main contributions of our study are outlined and some potential avenues for future research are described.

5.2 Background and Related Work

In the first six months of the COVID-19 pandemic, Langton et al. [155] analyzed the alterations in different crime rates in England and Wales at an aggregate level of England and Wales as one. Their findings indicated that, with the exception of anti-social behaviour and drug-related crimes, there was a significant drop in all crime categories following the implementation of lockdown measures. However, as these restrictions were eased, many crimes saw an increase and it appears that residential burglaries might not resume their usual rates anytime in the near future. On the other hand Langton et al. [155] reported that offences like robbery, violence and sexual offences did witness a swift return to their pre-pandemic levels. Similarly, Langton et al. [156] examined crime changes in England and Wales for the first seven months of the pandemic at the small-scale level. Their findings revealed that the drop in crime during the lockdown predominantly stemmed from a few specific areas, notably city centres with historically high crime rates. These trends can be attributed to the opportunity structure in those areas. However, even with the easing of lockdown restrictions, crime rates in these high-crime areas did not spike significantly and remained below the usual rates, even when areas with lower and medium crime rates reverted to their normal levels. In the study by Frith et al. [97] the authors focused on crime data spanning from January 2019 to September 2020 to assess the pandemic's influence on burglary crime within the London Metropolitan area at the borough level and hourly basis. The study uncovered a decrease in burglary incidents throughout the pandemic, particularly during the daytime. Halford et al. [122] analyzed the different crime types (including violence and sexual offences, assault, public order, criminal damage and arson, vehicle theft and burglary) in one UK police force region, contrasting them with 5-year average rates. Their findings highlighted diverse timings for shifts in various crime categories; all except vehicle crimes began to decrease after the World Health Organization's declaration of a global pandemic on March 11^{th} of 2020. By one week after the March 23^{rd} lockdown, there was a significant reduction in all crime categories, albeit with discrepancies. Halford et al. [122], Al-Sabbagh et al. [7] suggest that these changes in crime rates were predominantly influenced by changes in people's movement patterns and locations respectively. In a study conducted by Neanidis and Rana [199], the researchers explored how lockdown measures affected ten different categories of crimes, including burglary, criminal damage and arson, drugs, vehicle crimes, other thefts, possession of weapons, robbery, shoplifting, theft from the person, and violence and sexual offences, at the local authority level in England spanning from May 2013 to May 2021. Their research showed that, unlike localized lockdowns, nationwide lockdowns had a substantial impact on the trends in reported criminal activities, with the initial nationwide lockdown having the most noticeable effect. Furthermore, their investigation revealed that national lockdowns resulted in a significant decline in all the examined categories of crimes, except for anti-social behaviour and drug-related offences, which saw an increase. While Neanidis and Rana [199] assessed the impact of lockdowns on various crimes across different local authorities, their work assumed a uniform effect for each lockdown across these regions. This approach has potential limitations such as overlooking spatial variations in response to the lockdowns.

Moreover, other studies have investigated the impact of COVID-19 on specific crimes through the lens of criminal theories, including Routine Activities Theory (RAT), General Strain Theory (GST) and Situational Action Theory (SAT). RAT [63] suggests that crimes are not random occurrences but are instead either planned or opportunistic actions. Criminal events occur when three key elements converge in time and space: a motivated offender, a vulnerable target (such as a person or property seen as attractive to a potential offender), and a lack of guardianship (such as the limited presence of authority figures like police or school officials to deter such incidents). When all three elements are present simultaneously, the likelihood of a criminal event increases, whereas the absence of one factor reduces the opportunity for crime. The enforcement of COVID-19 containment policies and the practice of social distancing had repercussions on individuals' activities, crime patterns, and emotional states. Research indicates that RAT is linked to a decline in certain crime types, such as thefts, robberies, homicides, and certain group-based offences [30, 45, 189, 216, 40, 256]. General Strain Theory (GST) [2] explains how encounters with stress can potentially result in acts of violence and criminal behaviour. According to GST, individuals may experience different types of stress, such as the failure to achieve valued goals, exposure to negative stimuli like abuse, or the removal of positive stimuli. These strains can trigger strong negative emotions and mental health issues. To cope with stress, individuals may employ various strategies, including emotional (e.g., substance abuse), cognitive (e.g., downplaying adversity), and behavioural (e.g., seeking social support or engaging in criminal behaviour) mechanisms. Under certain conditions, particularly when legitimate coping strategies are lacking, individuals are more likely to resort to violent and criminal behaviours. The COVID-19 pandemic has undoubtedly given rise to different strains and stresses. The implementation of lockdowns can be perceived as a negative influence. The loss of loved ones or financial difficulties also deprives individuals of positive stimuli. Recent research has delved into the impact of the pandemic's stressful conditions, leading to an increase in mental health problems like depression and anxiety in both adolescents and adults, primarily due to heightened social isolation and stress [172, 64, 180, 309, 61]. Indeed, Zhang et al. [313], Campedelli et al. [46] have shown that the stress and negative emotions arising from the pandemic potentially contributed to an upsurge in violent crimes. Furthermore, it has been shown that there is a growth in intimate partner violence within many families due to the economic impact of the COVID-19 pandemic and the additional stressors introduced by social distancing measures [313, 30]. Other studies have demonstrated that alcohol and drug usage has risen among both young individuals and adults as a strategy for dealing with the challenges posed by the pandemic [86, 81, 141, 277]. Situational Action Theory (SAT) [290] explains the reasons behind criminal behaviour and, more broadly, why individuals adhere to or violate common rules of conduct. According to SAT, the causes of human actions are rooted in situational factors. People act the way they do based on their personal characteristics and the specific features of the environments they find themselves in. The theory also suggests that humans are fundamentally guided by rules and may commit a crime when they perceive it as an acceptable course of action given the situation, especially when no significant deterrents are present. Alternatively, individuals might engage in criminal behaviour when they fail to uphold their own moral standards (i.e., fail to exercise self-control) in situations where external pressures influence them to act against their own values [291]. Several studies have been conducted to examine the impact of COVID-19 pandemic policies and how these have altered situational environments, resulting in higher crime rates [200, 46, 9].

We believe that our research can provide additional support to the assertion that lockdowns in England and Wales significantly influenced the nature of criminal behaviour, as observed through the lenses of RAT, GST and SAT. Different local authorities possess varying demographics and socio-economic statuses, which can result in differing perceptions of injustice and levels of moral engagement. This leads to diverse levels of motivation for committing crimes due to factors like unemployment rates and the strictness of lockdowns. Moreover, there are varying levels of vulnerable targets and guardianship because of factors such as wealth. As discussed above, all of these factors could influence different crime patterns as predicted by RAT. Hence, we expect to see non-uniform impacts from interventions, such as lockdowns, on crime counts across the local authorities.

5.3 Methodology and Approach

In this section, we provide an overview of the input datasets, including the crime dataset and the COVID-19 stringency index utilized in our study. We also elaborate on the methodology employed to assess the impact of lockdown strictness on crime.

5.3.1 Study Area and Data

England is geographically divided into 9 geographical regions with Wales being divided into 4 similar regions. These regions are further subdivided into a total of 339 lower-tier local authorities: 317 in England and 22 in Wales. These local authorities include London Boroughs, Unitary Authorities, and both Metropolitan and Non-Metropolitan Districts. In this study, we utilised two data sources as follows, both of which are applicable to England and Wales:

- **Crime data:** Each local authority in England and Wales falls under one of the 42 territorial police forces. These police forces record and report areal data on criminal activities on a monthly basis [222]. The spatial scope of the data is restricted to Lower Layer Super Output Areas (LSOA) which form a geographic hierarchy designed to enhance the reporting of small area statistics in England and Wales [195]. For our study, we collected crime data [275] spanning from January 2015 to May 2023. This period of time spans pre-pandemic, pandemic, and post-pandemic periods. We have aggregated the data to the local authority level. Table 5.1 provides a thorough summary of various crime categories, along with their respective

Crime category	Description
Anti-social behaviour	Personal, environmental and nuisance anti-social behaviour
Bicycle theft	Taking without consent or theft of a pedal cycle
Burglary	Person enters a house or other building with the intention of stealing
Criminal damage and arson	Damage to buildings and vehicles and deliberate damage by fire
Drugs	Offences related to possession, supply and production
Possession of weapons	Possession of a weapon, such as a firearm or a knife
Public order	Offences which cause fear, alarm or distress
Robbery	Offences where a person uses force or threat of force to steal
Shoplifting	Theft from shops or stalls
Theft from the person	Crimes that involve theft directly from the victim, without the use or threat of physical force (including handbag, wallet, cash, mobile phones)
Vehicle crime	Theft from or of a vehicle or interference with a vehicle
Violence and sexual offences	Offences against the person such as common assaults, grievous bodily harm and sexual offences

Table 5.1: Crime categories from open police recorded crime data. See Police UK [222] for more details.

explanations. Although the Police UK website `https://data.police.uk/data/` offers the most detailed criminal reporting at a small-scale area throughout the UK, there are certain limitations within the period of our study. For instance, Greater Manchester Police has not submitted crime data to Police UK since July 2019 due to an IT system change. Additionally, crime data from Devon and Cornwall Police has not been made available since November 2022. There are more details on the Police UK website Police UK [223]. As a result, we have had to exclude local authorities in Greater Manchester entirely from our analysis. Additionally, our model employs crime data only up until November 2022, as all police forces, except for Greater Manchester, have at the time of writing finalized their reports up to that point (see Figure 5.1).

- **Oxford Coronavirus Government Response:** The Oxford Stringency Index (SI) is a comprehensive measure designed to assess the strictness of government policies worldwide from 3rd January 2020 until 31st December 2022 [121]. It encompasses nine response metrics, including school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal

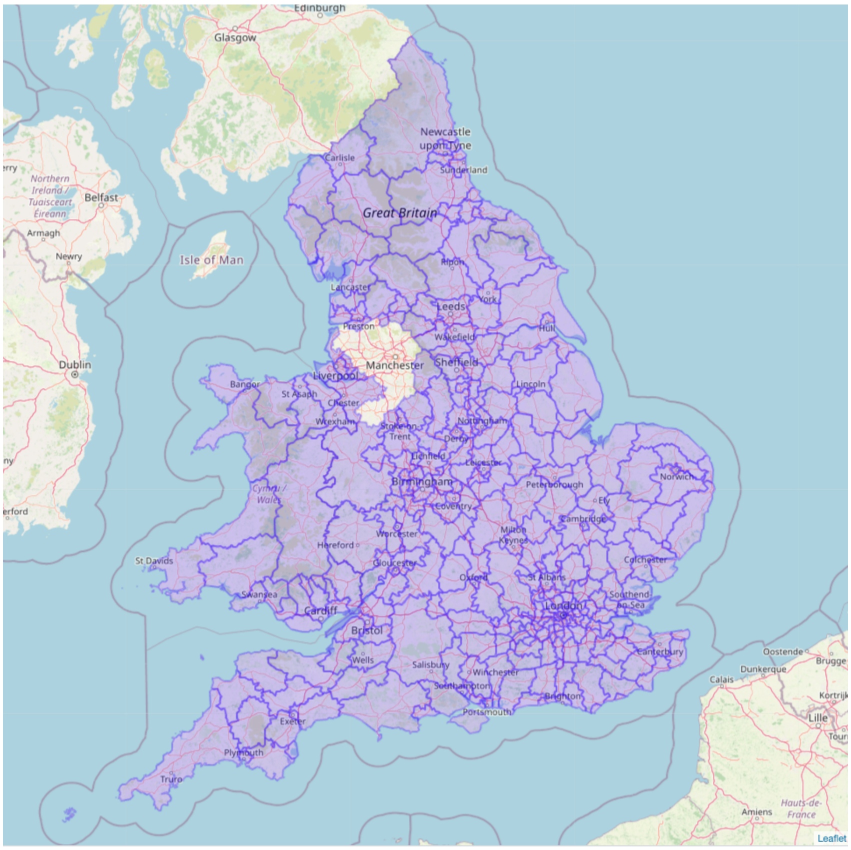


Figure 5.1: Map showing the study area of England and Wales, with local authorities outlined, excluding Greater Manchester due to data availability issues.

movements, and international travel controls. Each day, the index is computed as the average score of these nine metrics for each country, with values ranging from 0 to 100. This provides a quantitative representation of the spectrum from the least to the most stringent restrictions. As noted by Cross et al. [69], the SI fulfils the requirement for a standardized measure to compare the strictness of both national and international government responses across various days, and the index has gained widespread usage in assessing the impact of the COVID-19 pandemic and associated lockdowns on various problems, such as crime rates [129], stock market fluctuations [308], COVID-19 mortality [227], migration rates [126] and more. The methodology for calculating each metric is detailed in the work by Hale et al. [121] (For further details, the dashboard provided by Hale et al. [121] can be consulted [213]).

We observed that the Oxford Coronavirus Government Response Tracker [120] provided the daily SI for the entire UK, rather than reporting it separately for each country. Therefore, for the two countries under examination in this study, we utilize the UK's SI. To create monthly SI values for the UK, we computed the average index

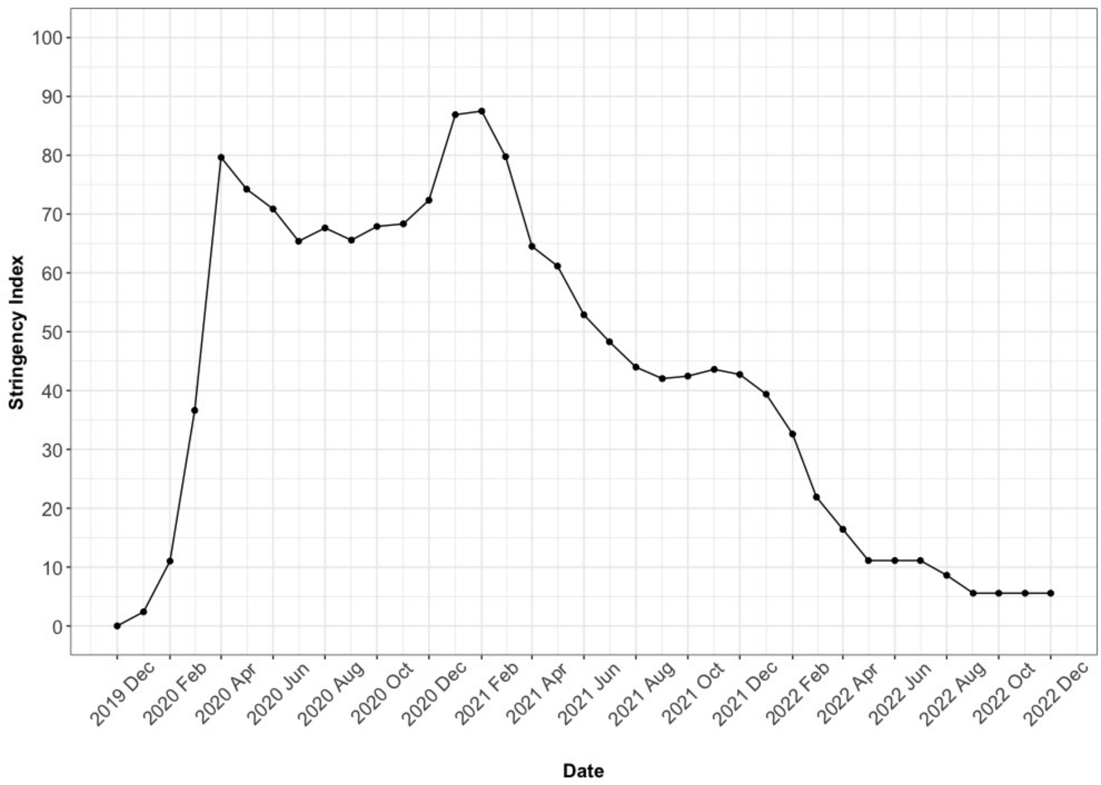


Figure 5.2: Variation in the stringency index (SI) in the UK between the years 2020 and 2022.

for each month, which aligned with the temporal resolution of our crime data. The changes in the SI, for the UK, from December 2019 to December 2022 are illustrated in Figure 5.2.

5.3.2 Spatio-temporal Modelling

We utilize a Bayesian spatio-temporal model to evaluate different crime types over time and space within England's major regions, as mentioned in Section 5.3.1. Our aim is to estimate the impact of restriction policies on the counts of various crime types within each local authority separately. The Bayesian modelling framework enables us to construct probabilistic models and appropriately quantify the uncertainty of estimated parameters using probability distributions. We adopted the model proposed by Bernardinelli et al. [26], which has seen extensive use in various applications, notably in crime mapping [168]. This model facilitates the modelling of area-specific trends, temporal trends, and the interactions between time and space and is fitted using the Integrated Nested Laplace Approximation (INLA) method as introduced by Rue et al. [241]. The R-INLA software [165] supports this model. To account for spatial and temporal dependencies,

the Conditional Auto-regressive (CAR) model, as described by Besag [28], Wall [279], was employed. For our specific study, the model can be described as:
Let $Y_{i,j}$ represent the number of crimes at location $i = 1, \ldots, n$ and time $j = 1, \ldots, J$. The model can be expressed as:

$$Y_{i,j} \sim Poisson(\lambda_{i,j}) \tag{5.1}$$

$$\log(\lambda_{i,j}) = \alpha + \eta_{q[j]} + (\beta + \delta_i) \times t_j + \gamma_i \times SI_j + u_i \tag{5.2}$$

where:

- $\lambda_{i,j}$ is the time and area-specific expected value of crime.
- α is the intercept.
- $\eta_{q[j]}$ represents the effect of the quarter of the year at time j, capturing the seasonality effect.
- β captures the overall temporal trend as the mean linear effect of time.
- δ_i denotes the space-time interaction effect.
- γ_i represents the area-specific effect of the stringency index.
- SI_j is the stringency index at time j.
- u_i is the spatial random effect.

Bayesian models necessitate the definition of prior distributions for the model parameters. Upon fitting, these parameters are updated using the data, resulting in posterior distributions. In our model, we opted for the default prior distributions specified in INLA. Non-informative priors for the parameters α and β are Gaussian with a mean of 0 and a variance of 10^6. Hierarchical priors for δ_i and γ_i follow $N(0, \sigma_\delta^2)$ and $N(0, \sigma_\gamma^2)$ independent and identically distributed (i.i.d) Gaussian distributions, respectively. For the spatial random effect u_i, we utilized the prior introduced by Besag et al. [29], which is:

$$u_i \mid u_{z \neq i} \sim N\left(\frac{1}{n_i}\sum_{z \sim i} u_z, \frac{\sigma_u^2}{n_i}\right)$$

where $z \sim i$ indicates all neighbors of region i, and n_i is the total number of neighbors. σ_u^2 represents the variance of the spatial random effect. We used the default non-informative priors for the hyper-parameters defined in INLA as follows:

$$\log\frac{1}{\sigma_\delta^2}, \log\frac{1}{\sigma_\gamma^2}, \log\frac{1}{\sigma_u^2} \sim \log\gamma(1, 0.00005)$$

5.4 Results and Discussion

Since May 2022, the dedicated coronavirus team in the UK Government no longer exists [274], due to changes in the pandemic situation reflecting shifts in the pandemic landscape such as rising population immunity through vaccination and prior infection alongside a decrease in the COVID-19 morbidity and mortality rate. This suggests a return of individuals in the UK to their usual routines and lifestyles. There is now a renewed focus on comprehending the spatio-temporal patterns of different crime types. As societies adjust to a post-pandemic world, understanding how crime patterns have evolved or remained constant during this period has become increasingly important.

In this section, we first provide graphical representations of crime patterns in England and Wales for various crime types over a period of nine years (January 2015 to May 2023) at the local authority level in order to address RQ1 and RQ2. These visualizations show the crime data and illustrate yearly and seasonal fluctuations and geographical differences for each crime type. Our main goal is to explore crime trends before, during, and after the pandemic. To study these trends, we use two different visualizations: time series plots and heatmaps. Figure 5.3 displays time series plots that visualize the total count of specific crime types across England and Wales. For a deeper analysis of whether the crime trend is consistent among the majority of local authorities or is predominantly influenced by a few, we turn to heatmaps. Figure 5.4 displays the heatmaps, which offer a detailed representation of each crime across the 339 local authorities. The UK government issued a nine-character code, with one letter followed by eight numbers, to uniquely identify each local authority. Displaying all 339 local authorities with their codes on the heatmaps would be overwhelming and hard to read. To address this issue, we convert each local authority code into a unique number ranging from 1 to 339. This helps in simplifying the visualization. Moreover, local authorities that are neighbours and share borders have numbers that are close together. For instance, local authorities numbered 1 and 2 are neighbours. We scale the crime time series for each local authority to make them comparable for visualization purposes. As such, the heatmaps use z-values to present the crime data, providing insights into how crime counts differ from the average across regions and time. The colour intensity in each cell indicates the distance from the time series overall mean, with green showing negative z-values (below the average) and red showing positive z-values (above the average). Due to the absence of crime data from the Devon and Cornwall police force after November 2022, certain local authorities are represented in grey, indicating missing values, on the heatmaps for subsequent months. There are two distinct vertical dashed lines in each plot. These mark critical points in recent history: the start of the first national lockdown in March 2020 and the end of the pandemic in May 2022 in the UK which had notable impacts on crime trends.

We next delve deeper into understanding how different types of crimes were affected by the pandemic across various local authorities in England and Wales in order to address RQ3. We use maps to depict the influence of the stringency index on crime, as calculated by our model described in Section 5.3.2. Figure 5.5 displays these maps, highlighting the effects of stricter lockdown measures on each crime category throughout the study area. They also help us pinpoint local authorities that experienced a significant impact in the effects of the stringency index compared to others. As depicted in Figure 5.5, for each crime category, we have presented three maps, from left to right, corresponding to the estimated stringency index effects at the 2.5%, 50%, and 97.5% cumulative probability levels. The values within the 2.5% and 97.5% maps represent the 95% credible interval for the stringency effect on that particular crime type within each local authority. Table 5.2 presents our model's goodness of fit as measured by the R^2 and RMSE criteria, along with descriptive statistics for each type of crime. In the following sections, we discuss our findings for each crime type separately and explore potential drivers behind the observed patterns.

Crime category	**Total count**	**Mean**	**Std.**	R^2	**RMSE**
Anti-social behaviour	11461783	357.28	340.07	0.92	94.62
Bicycle theft	645018	20.96	29.40	0.87	10.37
Burglary	2634785	82.25	90.52	0.93	22.72
Criminal damage and arson	3972475	123.77	112.49	0.95	23.55
Drugs	1207719	37.73	46.79	0.90	14.22
Possession of weapons	307875	10.06	13.58	0.87	4.80
Public order	3015607	94.07	112.19	0.92	30.31
Robbery	514907	17.64	34.90	0.92	9.00
Shoplifting	2505011	78.24	77.66	0.93	19.96
Theft from the person	690501	23.13	79.19	0.92	20.57
Vehicle crime	3031008	94.57	115.54	0.94	27.35
Violence and sexual offences	12909980	401.61	412.53	0.96	78.63

Table 5.2: Offences categories and corresponding descriptive statistics, and the model's goodness of fit for each category for January 2015 to May 2023. For consistence, in column one, we use the same crime category names as used by Police UK.

5.4.1 Anti-social behaviour crime

Figure 5.3(a) shows the total instances of anti-social behaviour crimes spanning the period from January 2015 to May 2023. The plot exhibits seasonality, with consistent and predictable changes occurring every year. Notably, each year, the pattern exhibits an increase starting from March, peaking in July, and declining until December. We observe an overall downward trend with some fluctuations leading up to the period just before the pandemic. Then a conspicuous rise in the total count of anti-social behaviour crimes coincides with the onset of the COVID-19 pandemic (shown by the red dashed line, indicating March 2020). This suggests that the pandemic and the ensuing lockdown measures plausibly promoted anti-social behaviour offences, leading to a temporary increase. According to Figure 5.4(a), the majority of local authorities have experienced similar patterns, demonstrating that our deductions are not solely based on a few regions. Furthermore, Figure 5.5(a) illustrates the variation in the impact of the stringency index on anti-social behaviour crimes across different local authorities in England and Wales. This effect appears to be relatively consistent and positive, with some regions experiencing greater impacts.

Subsequent to the initial surge (April and May 2020), a notable reduction in instances of anti-social behaviour crimes becomes apparent. The most pronounced reduction occurs between December 2020 and January 2021, coinciding with the period of the highest stringency index. Interestingly, despite the increasing impact of stricter lockdown measures during the initial increase, the higher stringency index in December and January does not lead to an increase in the overall count of anti-social behaviour crimes. This counteractive effect could potentially be attributed to the previously discussed seasonal trend, where the total count of this type of crime typically reaches its lowest point in December and January each year compared to other months. Subsequently, this declining trend persists beyond the conclusion of the pandemic (depicted by the green dashed line representing May 2022). Therefore, despite the initial surge in criminal activities brought about by the start of the pandemic, it is evident that this particular type of crime maintains its ongoing downward trajectory that has been established since 2015. The alteration in the trend of anti-social behaviour crimes during the onset of the pandemic can be attributed to certain individuals resisting the strict lockdown measures. Moreover, the pandemic placed considerable strains on people's daily lives, including instances such as job losses, financial difficulties, the loss of loved ones, feelings of social isolation, concerns regarding vaccination, and a range of other pandemic-related anxieties [172, 64, 180, 309, 61]. These factors played a role with many individuals struggling with negative emotions. These emotions may have been intensified due to the lack of healthy coping mechanisms such as social interactions. This aligns with the core principles of the GST, as discussed in section 5.2. Additionally, the heightened stress and anxiety due to financial and emotional difficulties led to moral disengagement, where some individuals justified anti-social behaviour as a reaction to their own perceived injustices or frustrations with pandemic restrictions. Shifts in social norms during this period may have further contributed to these behaviours, as some people perceived anti-social actions as more acceptable under extraordinary circumstances, which is consistent with the principles of SAT. After the restrictions were eased, the trend seems to be now reverting back to its pattern before the pandemic.

5.4.2 Bicycle theft

According to Figure 5.3(b), a rising trend in bicycle theft is evident until 2018, followed by a subsequent decline. The presence of a noticeable seasonal pattern is also apparent, with certain months consistently showing higher rates of bicycle theft. This recurring pattern could be influenced by factors such as weather conditions (such as warmer months potentially leading to increased bicycle usage and subsequently more thefts), holidays, an influx of tourists, and other annual events. This aligns with RAT, suggesting that during periods of favourable conditions, the attractiveness of alternative transportation options like bikes and scooters increases, providing more opportunities for street criminals.

While temporary fluctuation can be observed - like a momentary reduction coinciding with the beginning of the pandemic (March 2020) unlike previous years these tend to balance out over the long run. When analyzing the longer period of nine years (2015-2023), the total count of bicycle thefts demonstrates a consistent decline post-2018. It appears that the pandemic did not alter the existing trend of bicycle theft observed prior to the pandemic. This suggests that, despite external influences and year-to-year variations, the broader pattern of bicycle thefts has remained relatively stable. This viewpoint contrasts with the conclusions drawn from some other studies [155, 3]. While these studies have emphasized specific short-term increases in theft rates, our analysis offers a more holistic perspective by spanning the entire duration of the pandemic and its aftermath. Through this comprehensive examination, we have observed a persistent decrease in the overall trend since 2018. According to Figure 5.4(b), this holds true for the majority of local authorities.

In Figure 5.5(b), we depict the variation in the impact of the stringency index on bicycle theft crimes across local authorities in England and Wales. This effect shows notable disparities among the local authorities. Notably, certain areas, such as those within the City of London, exhibit significant positive values of this effect, while others exhibit significant negative values of the effect. This can be explained by the fact that there are more households in the city of London without access to a car or van compared to the rest of England and Wales [204]. As a result, their primary transportation choices are limited to public transportation like buses and subways, taxis, or bicycles. During the lockdowns the government either partially suspended public transportation services or reduced their capacity [68] and this encouraged more people to opt for bicycles. This shift in transportation preferences has altered the opportunity structure for bike thefts in central London.

5.4.3 Burglary

Figure 5.3(c) shows no prominent trend from 2015 to 2019 in burglary incidences. However, in 2019, a declining trend begins to emerge, and this downward trajectory becomes more pronounced with the onset of the pandemic. Notably, there are two distinct declines since the start of the pandemic. The first is a substantial drop at the beginning of the pandemic followed by another drop in January/February 2021. These declines are aligned with periods when the stringency index reached its peak values. These drops can be attributed to the fact that more individuals were staying at home during these times likely resulting in fewer unattended targets for burglars. Figure 5.4(c) confirms that the pattern is fairly consistent across all local authorities.

However, burglary incidents have not reached pre-pandemic levels and remain significantly lower. Several factors could account for this new sustained trend: (1) increased residence occupancy: the adoption of remote work and extended periods spent at home due to the pandemic have reduced the opportunities for burglars which aligns with the concepts of RAT. (2) Elevated security measures: due to the effects of COVID-19, more people have been staying at home, prompting a heightened interest in fortifying their residences and purchasing security-related equipment they might have postponed previously. This surge in home security and CCTV system acquisitions is evident in the UK, where there is approximately one camera for every 13 individuals [307]. Furthermore, this number is projected to escalate significantly from 2021 to 2025 by around 26% [285]. Hence, homeowners, exhibiting increased security awareness during the pandemic, have embraced these upgraded security solutions. These measures continue to deter burglaries by decreasing the pool of susceptible targets, aligning with the principles of RAT, even in the post-pandemic phase.

The figures also unveil a seasonal pattern, with heightened burglary counts in specific months such as October and November, while counts are relatively lower from March to September. This could be attributed to various factors, such as increased shopping activities during October and November due to sales seasons like Black Friday, Christmas, and New Year, leading to more valuable items in homes. Additionally, the decrease in daylight hours during these months may offer cover for burglars who aim to avoid being seen. With respect to the effect of the stringency index, Figure 5.5(c) displays the variation in the effect on burglary crimes in various local authorities in England and Wales. This effect seems to be uniform and negative across most local authorities. However, it is worth noting there are a few local authorities, namely Monmouthshire and Newport, that exhibit a positive effect. At the time of writing this paper, the reason for the positive effect in these regions is unclear to us and warrants further investigation, which we defer to future work.

5.4.4 Criminal damage and arson

Figure 5.3(d) illustrates the total count of criminal damage and arson cases spanning from 2015 to 2023. During the pandemic period, there are two noticeable declines in the data, one occurring at the commencement of the pandemic (indicated by the red dashed line), and the other in February 2021. These drops coincide with the peaks of the stringency index and stricter lockdowns. Following the second drop we can see that the trend rebounds. Figure 5.4(d) illustrates that this behaviour occurred in the majority of the local authorities. It appears that the downward trajectory of criminal damage and arson crimes since late 2017 has persisted. The pandemic's impact on this trajectory seems to be a temporary decrease rather than a lasting change.

Figure 5.5(d) demonstrates the variation in how the stringency index affects criminal damage and arson crimes in various local authorities across England and Wales. This effect seems to be negative and consistent across various local authorities. However, a minority of the local authorities changed colour from blue to red in the 2.5% and 97.5% panels respectively. This should caution us against drawing conclusions with high certainty about the impact of the stringency index in these areas.

5.4.5 Drugs

As depicted in Figure 5.3(e), the total count of drug crimes in England and Wales follows a fluctuating pattern, initially displaying a downward trend until the end of 2016. Subsequently, the trend reverses and begins to rise, gaining momentum by the onset of the pandemic, with a peak in May 2020. However, this surge subsides, and the trend begins to flatten, eventually aligning closely with its pre-pandemic levels from mid-2021 onward. This suggests that the pandemic and subsequent lockdown measures influenced the trajectory of drug-related offences, leading to an increase in such incidents. This increasing impact fades as pandemic measures are relaxed. Moreover, Figure 5.4(e) reveals that drug crime exhibits either low seasonal fluctuations or none that are clearly discernible. This trend can be attributed to the majority of the local authorities.

Multiple factors might have contributed to the heightened levels of drug-related crimes during the initial year of the pandemic. These factors are outlined as follows: (1) Psychological well-being: the pandemic's impact on mental health could has contributed to heightened drug consumption and this subsequent increase [172, 64, 180, 309, 61] aligns with the principles of GST, RAT and SAT. (2) Shift in law enforcement focus: law enforcement agencies might have redirected their attention to street-level activities during the pandemic's early stages, leading to heightened proactive efforts in drug-related operations. This adjustment could have been facilitated by the increased visibility of dealers and suppliers, who encountered greater difficulty moving around freely due to the lockdown measures [49, 123]. Given that these two factors have almost reduced post-pandemic, this could explain why the trend in drug crimes has returned to its pre-pandemic pattern. According to Figure 5.5(e), it is evident that the impact of the stringency index on drugs crime is somewhat uniform and positive in the majority of local authorities. Nevertheless, it is noteworthy that several local authorities in the North West of England and Pembrokeshire exhibit significant negative values of this effect.

5.4.6 Possession of weapons

Figure 5.3(f) displays a significant upward trajectory preceding the pandemic, with the bulk of the increase occurring between March 2016 and March 2019 [202]. As the pandemic began, the trend shifted direction, resulting in the lowest point since mid-2017 in February 2021, coinciding with the highest value of the stringency index. This decline may be linked to the implementation of stricter lockdown measures, which shifted law enforcement's attention towards public spaces. Consequently, there was an elevated risk for criminals to be apprehended by authorities for carrying weapons. This heightened risk aligns with the concepts of the RAT, leading to a decrease in the likelihood of this crime occurring. Starting in mid-2021, the government initiated a relaxation of some pandemic measures (for more detail, see Figure 5.2). Subsequently, the trend for weapon possession crimes began to rise once more. This suggests that the pandemic's effect on this crime category was not persistent. However, it is worth noting that, according to Figure 5.4(f), there are different clusters of local authorities. Some peaked between 2016 and 2018, then experienced a decline. Many peaked between 2018-2019 and declined with the onset of the pandemic, never returning to pre-pandemic levels. In contrast, a significant number reached their peaks post-pandemic.

Figure 5.5(f) illustrates the impact of the stringency index on weapon possession crimes in local authorities across England and Wales. As shown in the figure, numerous local authorities shifted from blue to red in the 2.5% and 97.5% plots, respectively. This includes a zero-effect interval, meaning we cannot definitively claim whether the effect has been positive or negative for these regions. Conversely, in certain regions like Uttlesford (England) the effect is notably negative, while in places like Neath Port Talbot (Wales), it is significantly positive.

5.4.7 Public order

Figure 5.3(g) presents the total count of public order crimes over a span of nine years and there is a discernible upward movement in the trend. This could potentially be attributed to economic difficulties and mental well-being [67, 181, 250]. Additionally, the plot shows a clear seasonal pattern with certain months consistently exhibiting elevated occurrences of public order crimes, such as June and July, while other months show a decrease, including the period from December to February. This seasonality could potentially be attributed to various factors, including notable public events like Black Lives Matter rallies and far-right counter protests (during June and July) [115], as well as holiday seasons like Christmas and New Year when individuals often opt to stay indoors with their families, participating in seasonal celebrations. This shift towards indoor activities results in fewer outdoor engagements and gatherings and fewer opportunities for conflicts or disruptions that could potentially escalate into public order crimes.

The indicated upward trend experiences two declines. There is one minor decline at the beginning of the pandemic and another decline in January/February 2021. These drops coincide with the periods when the stringency index reached its peak, indicating that the implementation of lockdowns had an effect on the occurrence of public order crimes. However, as time progressed and certain individuals disregarded government mandates, the count rose once again. This pattern is consistent with the principles of the GST, where individuals when confronted with these strains, opt for resistance against the government and causing fear and distress. Also, heightened stress and anxiety due to the pandemic, along with perceptions of injustice and moral disengagement, may have led individuals to justify their criminal behaviour as a reaction to their perception of overreaction by authorities, which aligns with the principles of SAT. Additionally, according to Figure 5.4(g), this pattern is evident for most local authorities, with only a small number of local authorities diverging from the mainstream trend. Overall, public order crimes have been persistently higher than pre-pandemic levels. This cannot necessarily be attributed solely to the lockdowns, as the rising trend predating the pandemic is also a factor. According to Figure 5.5(g), the effect of the stringency index on public order crimes in the local authorities of England and Wales is heterogeneous. The effect has been positive in many areas such as East Midlands while being insignificant or negative in other places like Shropshire and Stafford.

5.4.8 Robbery

Based on Figure 5.3(h), the robbery trend demonstrates a rise until March 2019, followed by a decline leading up to the pandemic. Subsequently, there are two noticeable drops: one coinciding with the initiation of the pandemic (highlighted by the red dashed line), and the other in February 2021. These findings correspond with the peaks of the stringency index and indicate a noticeable impact of the pandemic and its associated restrictions on the trend of robbery. Thereafter, the trend shows a partial rebound, and it continues to move in an upward trajectory. However, the levels post-pandemic have not managed to reach the heights observed in previous years. Figure 5.4(h) shows that this pattern holds true for the majority of the local authorities, and it is not dominated by a few outliers.

Several factors could explain the persistent lower number of robbery crimes even after the pandemic: (1) Shift in opportunities: the prevalence of remote work may result in fewer opportunities for street-level robberies due to reduced foot traffic. (2) Heightened security measures: the increased installation of CCTV cameras, alarm systems, and improved lighting in public spaces and residential neighbourhoods [307, 285, 217], could serve as deterrents, dissuading potential robbers and thus contributing to the decline in robbery crimes. There are some linkages to the discussion around burglary in section 5.4.3.

The impact of the stringency index on robbery crime throughout England and Wales is presented in Figure 5.5(h). According to the figure, the effect is negative with at least a 50% probability for the vast majority of the local authorities. However, examining the panel from left to right, we notice that many regions have shifted from blue to red. This shift indicates a non-negligible probability that the effect could be positive, which cautions against drawing definitive conclusions about the magnitude of the effect in those regions. Nonetheless, there is only one region, which is Neath Port Talbot (Wales), that exhibits a significant positive effect.

5.4.9 Shoplifting

Figure 5.3(i) reveals alternating phases of upward and downward trends in the shoplifting crime pattern prior to the pandemic, with the upward trend persisting until the end of 2017. Subsequently, the downward trend that commenced at the end of 2017 continues, marked by a significant drop at the onset of the pandemic. An additional decrease is noticeable in January/February 2021. These declines are likely attributable to the closure of numerous businesses and reduced in-person shopping. Consequently, it is reasonable to expect that opportunities for shoplifting diminished during this period and this observation aligns with the principles of RAT. After this decrease, the trend begins to rise, eventually surpassing the levels observed before the pandemic. Furthermore, Figure 5.4(i) indicates that this trend is consistent across the majority of local authorities. Similarly, Figure 5.5(i) illustrates consistent negative values in the impact of the stringency index on shoplifting crimes throughout England and Wales except for Sevenoaks and Gosport (both England) which experienced significantly positive impacts.

5.4.10 Theft from the person

Figure 5.3(j) illustrates a general upward trend in these incidents throughout the years until the advent of the pandemic. Two distinct drops in the pattern are apparent: one taking place at the beginning of the pandemic (marked by the red dashed line), and the other in January/February 2021, corresponding with the highest points of the stringency index. These drops can be attributed to the pandemic and the enforced lockdowns altering people's routine activities. With many individuals confined to their homes, limitations on public gatherings, and the closure of non-essential businesses, the opportunities for thieves have significantly diminished on the streets and in public areas. Following the mentioned pronounced declines, incidents of theft from the person began to rise once more, eventually reaching levels similar to those observed before the pandemic. This suggests that the alteration in the pattern of theft from the person crimes during the pandemic was not sustained which is consistent with the RAT.

Looking at Figure 5.4(j), we do not see evidence of a few regions dominating the overall trend. Instead, the majority of the local authorities exhibit similar patterns. Figure 5.5(j) displays the effect of the stringency index on theft from the person crimes throughout England and Wales. This effect seems to be negative and consistent across various local authorities. However, a minority of the local authorities changed colour from blue to red in the 2.5% and 97.5% panels respectively. This should caution us against drawing conclusions with high certainty about the impact of the stringency index in these areas.

5.4.11 Vehicle crime

As depicted in Figure 5.3(k), there is an increasing trend observed until 2019, followed by a subsequent decline. Two distinct drops in the trend of vehicle crimes are evident — one at the beginning of the pandemic (marked by the red dashed line), and another in February 2021, coinciding with the highest points of the stringency index. This suggests that the pandemic and the associated lockdowns had a substantial impact on vehicle crimes. As time progresses, the trend begins to rise again. However, the crime count in the post-pandemic period has not reached the levels observed prior to the pandemic's outbreak. According to Figure 5.4(k), this pattern is not uniform across all local authorities. There is noticeable heterogeneity; some local authorities have recovered their pre-pandemic levels more than others. The ongoing decrease in vehicle crime after the pandemic in certain areas can be attributed to several factors such as:

(1) Diminished vehicle utilization: With more individuals continuing to work from home in these areas post-pandemic, there is a reduction in the number of vehicles on the road, leading to fewer opportunities for theft.

(2) Heightened security measures: The increased deployment of CCTV cameras, coupled with improved lighting in public areas and residential neighbourhoods, elevates the risk of criminals being apprehended.

Furthermore, Figure 5.3(k) showcases a seasonal pattern. Specific months consistently exhibit heightened occurrences of vehicle crimes, while others show a decrease. This cyclic pattern could potentially be influenced by various factors such as weather. For instance, in colder months it is plausible that people might be more likely to use their vehicles for commuting due to unfavourable weather conditions. This increased vehicular activity could lead to higher instances of vehicle-related crimes. There are more cars on the road and parked in various locations. Holiday periods can see people travel and vehicles are left unattended, or other seasonal influences that are in accordance with the concepts outlined in RAT. In Figure 5.5(k), we present the impact of the stringency index on vehicle-related crimes across England and Wales. This impact is predominantly negative and consistent across most local authorities. However, West Suffolk (England) is an exception where the effect has been positive.

5.4.12 Violence and sexual offences

According to Figure 5.3(l), the total count of violence and sexual offences in England and Wales shows an overall ascending trend from 2015 to 2023. The upward trend observed over the years could be explained by several factors. These include a greater willingness of victims to report such crimes, including those from the past, along with improvements in the recording procedures by law enforcement [205]. Additionally, the surge in stress, anxiety, and challenges related to mental health [44] might contribute to an increased propensity for violent behaviours [189, 219]. This alignment with the GST and SAT suggests that these external pressures might intensify the likelihood of engaging in aggressive actions.

Two noticeable declines in the trend are observable, one occurring at the onset of the pandemic (indicated by the red dashed line), and the second one in February 2021, aligning with the peak values of the stringency index. These declines might be attributed to people adhering to government strict stay-at-home orders, resulting in fewer vulnerable targets on the streets and a reduction of these crimes (which is aligned with RAT). Subsequently, the count began to rise once more, resuming the upward trend observed before the pandemic. This pattern suggests that the pandemic's effect on the trend of violence and sexual offences was not enduring and the original trajectory persisted. According to Figure 5.4(l), the pattern holds true for the majority of the local authorities. However, it is worth noting that, similar to public order crimes, several regions experienced peak levels of violence and sexual offences in 2018. In Figure 5.5(l), we can observe the impact of the stringency index on violence and sexual offences across England and Wales. According to the figure, while the majority of local authorities experienced negative impact values, there are some local authorities in the middle and east regions of England that experienced positive impact values.

5.5 Conclusions and Future Work

The security of society, economic progress, people's daily routine, mental well-being, criminal activities, and more have all been profoundly affected by the unprecedented consequences of the recent COVID-19 pandemic across the globe. This study investigated the shifts in various categories of crime over a 9-year period from 2015 to 2023 for local authorities in England and Wales. It also considered the potential reasons behind these shifts and explored the impact of varying degrees of lockdown measures on different types of crime using a Bayesian spatio-temporal model.

The analysis of temporal patterns revealed that certain types of crimes in England and Wales underwent substantial alterations throughout the pandemic. These shifts were particularly pronounced when the stringency index was elevated, indicating greater constraints on citizens' mobility. This observation aligns with criminological theories like the GST, RAT and SAT, which posit that external constraints and opportunities can impact criminal behaviour. Additionally, for certain types of crimes, the alterations in their trend diminished as pandemic measures were eased, returning to their pre-pandemic trajectories. However, as of the time of writing this chapter, crime types such as burglary, robbery, and vehicle crime have not returned to their pre-pandemic levels. While the pandemic is a contributing factor to this ongoing change, there are other potential factors that may have contributed to the persistence of lower levels of these crimes, including increased occupancy of residences due to the adoption of remote work arrangements and heightened security measures implemented in both public and private spaces. We also discovered that contrary to the belief that the pandemic led to an increase in bicycle thefts, both the trend and the total count of this crime remained relatively stable and did not exhibit significant changes from the pre-pandemic trend and total counts. However, the only exception is London, where bicycle theft increased as a result of the pandemic. For shoplifting and theft from the person crimes, which were significantly influenced by business closures and restricted mobility, we observed a similar trend during the pandemic period. Both of these crime types witnessed a substantial decline initially, but as pandemic restrictions were eased and we approached the end of the pandemic, the incidences of these crimes began to rise, eventually returning to pre-pandemic levels. Although anti-social behaviour and drugs crimes differ significantly in nature, they both exhibited a significant increase at the onset of the pandemic. Subsequently, as pandemic restrictions

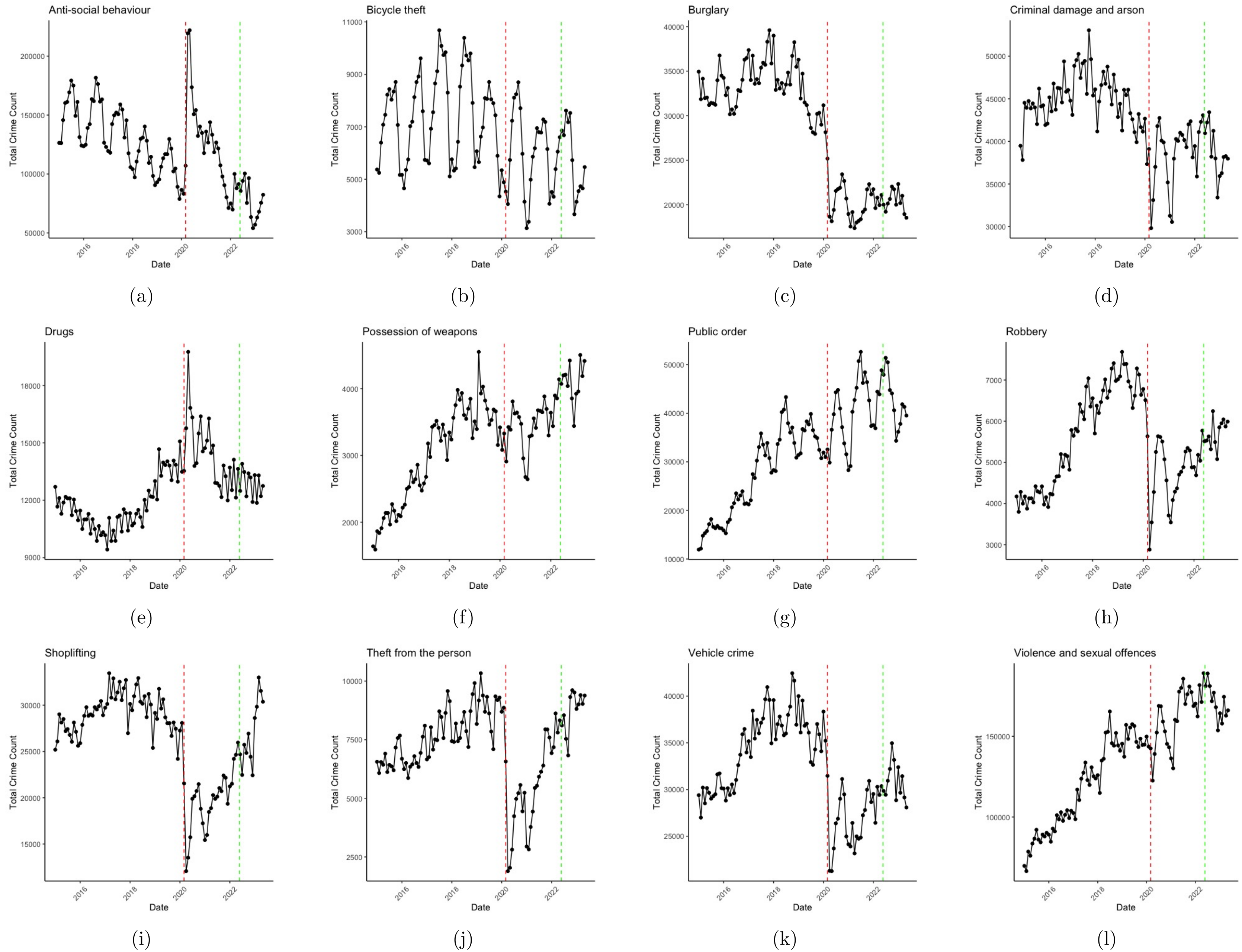
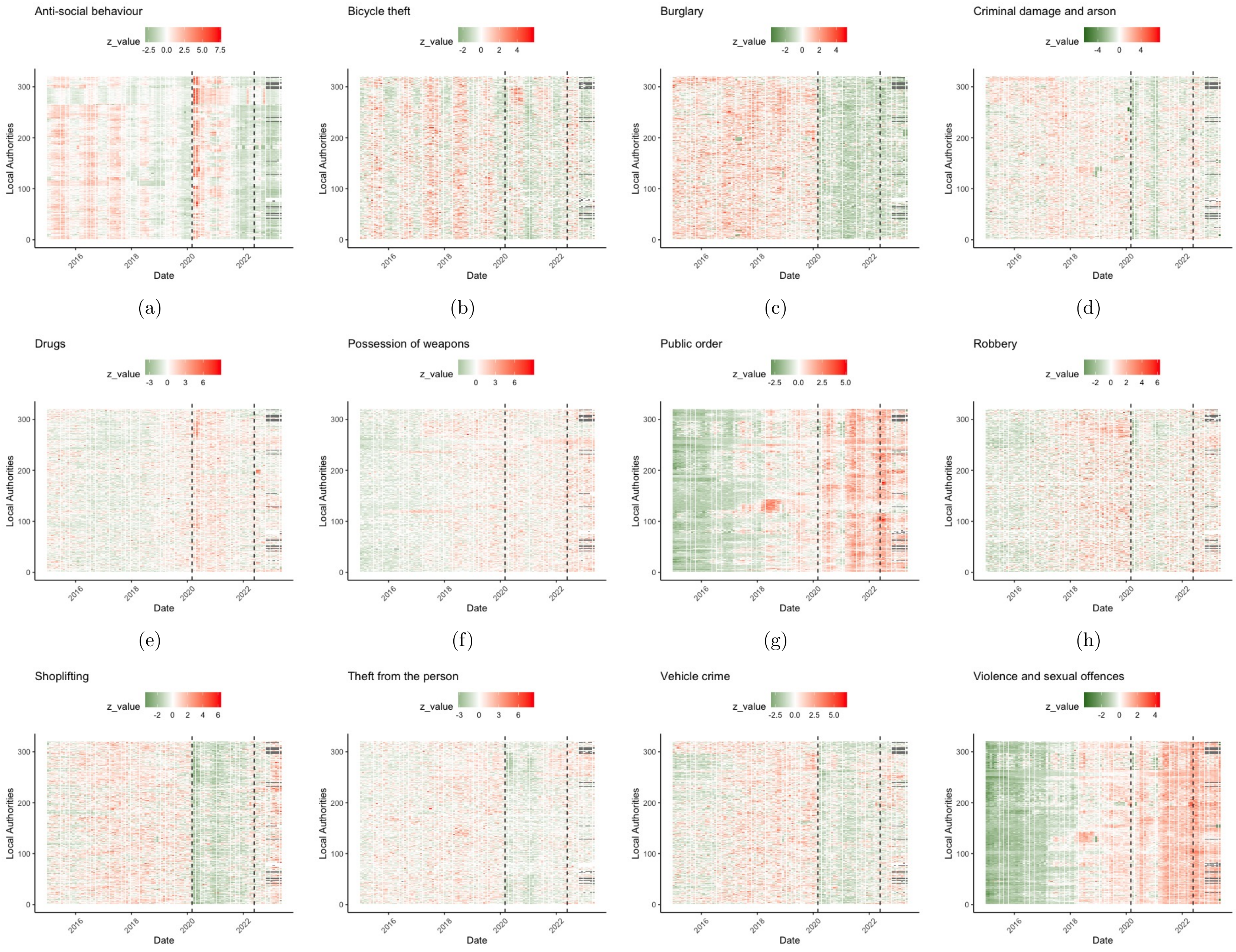
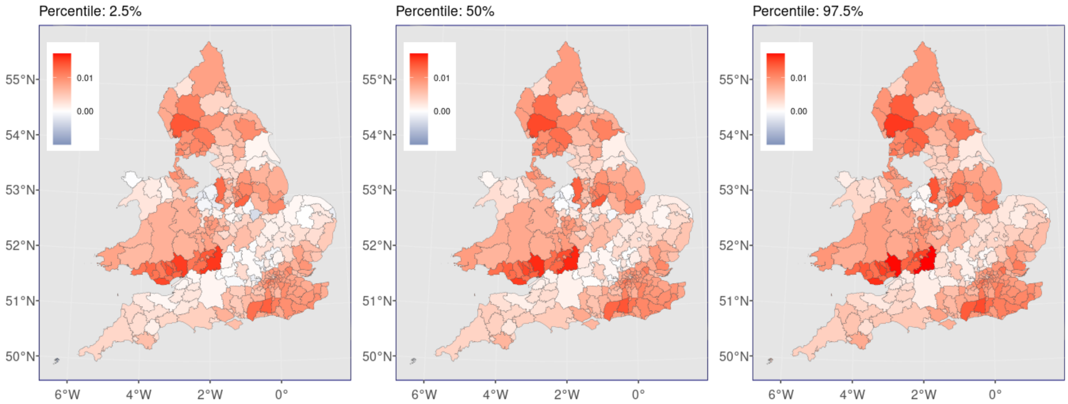


Figure 5.3: Temporal representation depicting diverse crime categories spanning the years 2015 to 2023 in England and Wales. The time series plots illustrate the total number of each crime type over the specified timeframe. The vertical red dashed lines denote the onset of the initial nationwide lockdown, while the green lines signify the conclusion of the pandemic.

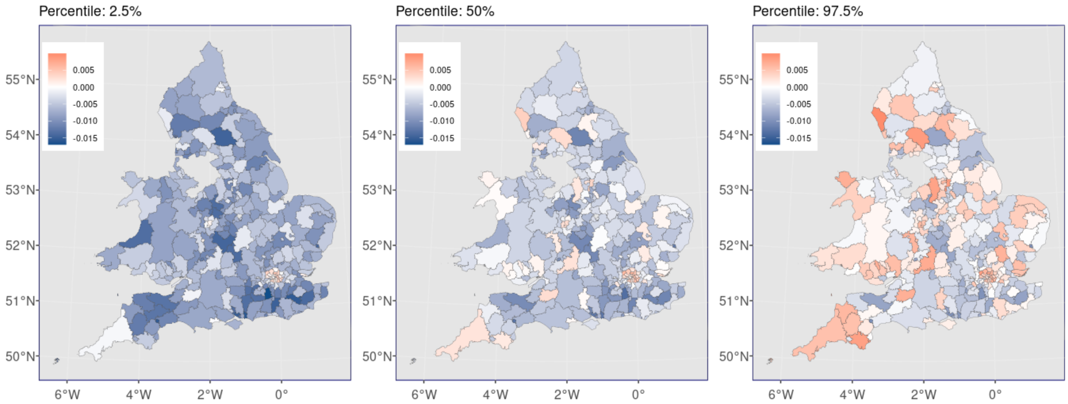


(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)

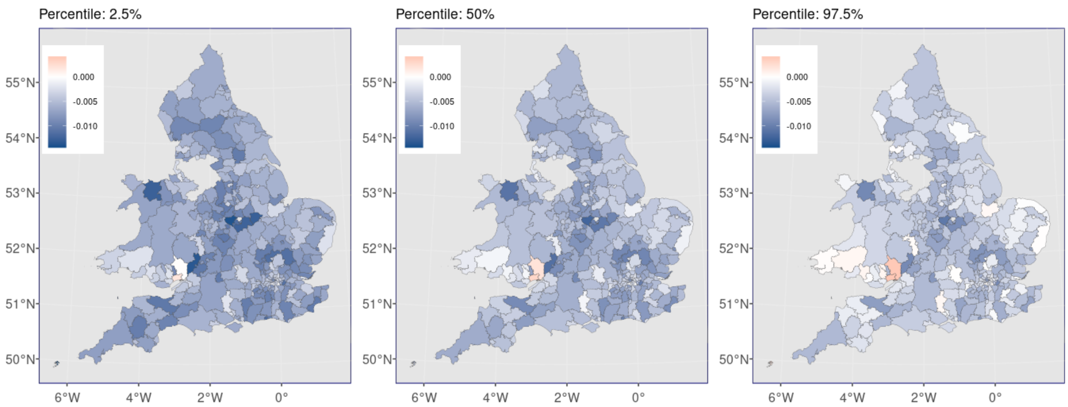
Figure 5.4: Spatio-temporal representation depicting diverse crime categories spanning the years 2015 to 2023 in England and Wales. The heatmaps depict the z-values associated with each crime type across varying local authorities and timeframes. Vertical dashed lines illustrate the commencement of the initial nationwide lockdown and the conclusion of the pandemic, respectively.



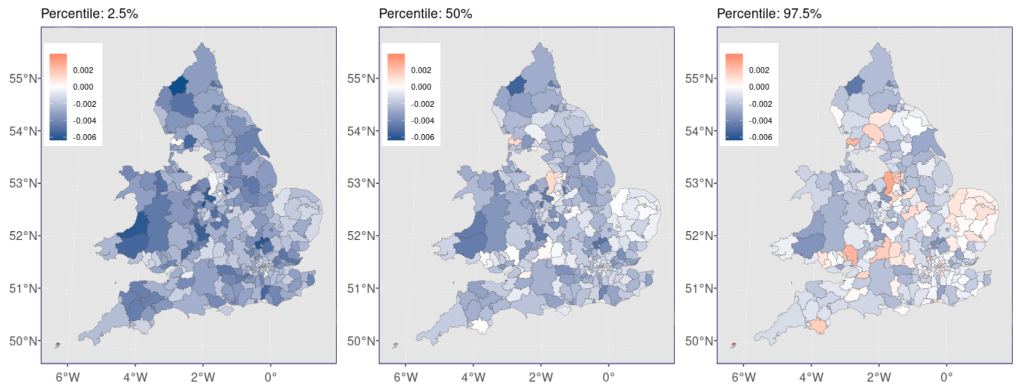
(a) Anti-social behaviour



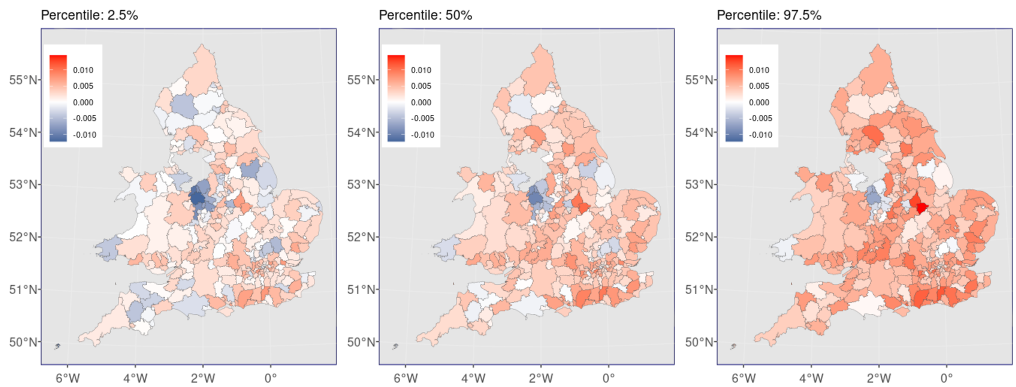
(b) Bicycle theft



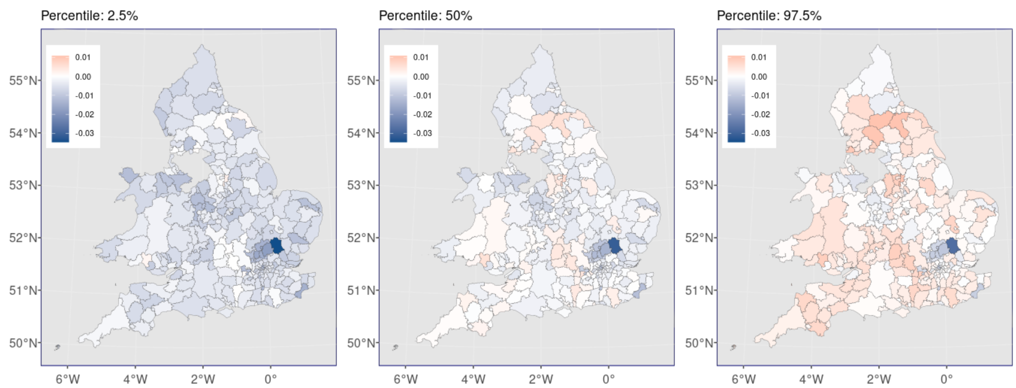
(c) Burglary



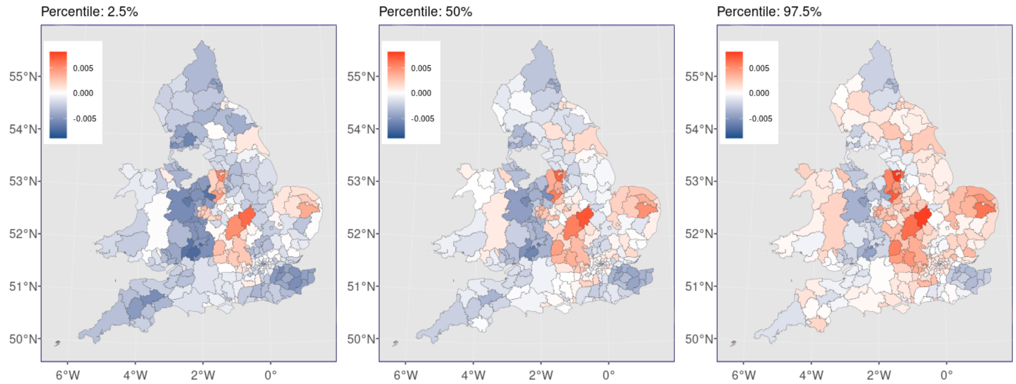
(d) Criminal damage and arson



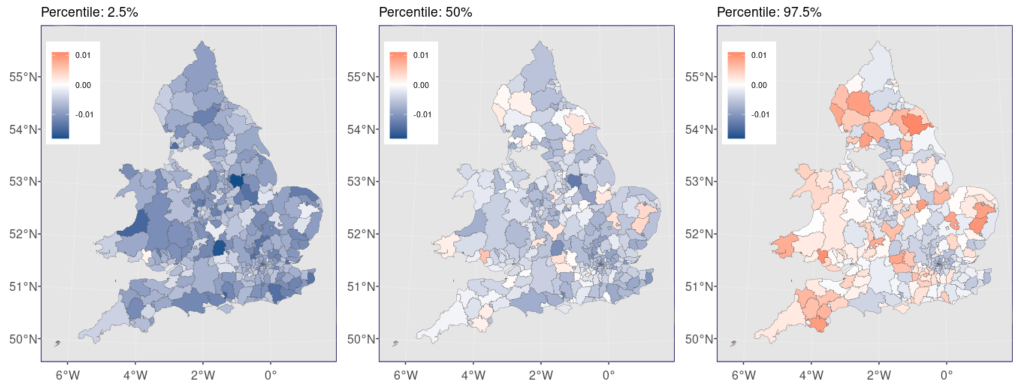
(e) Drugs



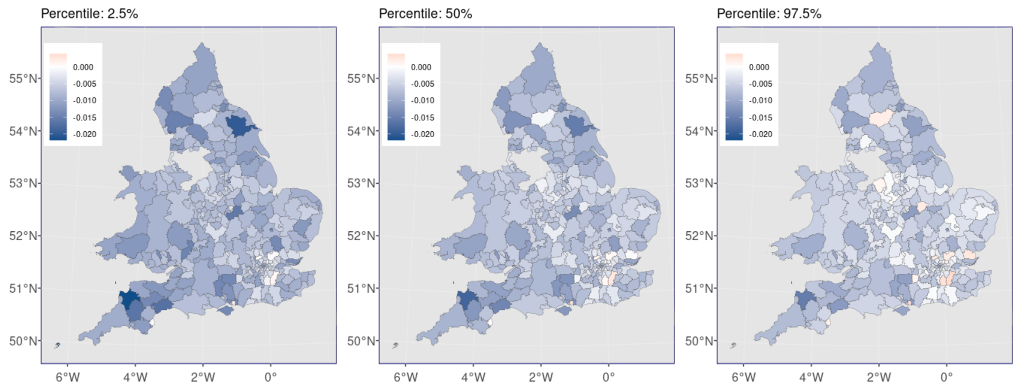
(f) Possession of weapons



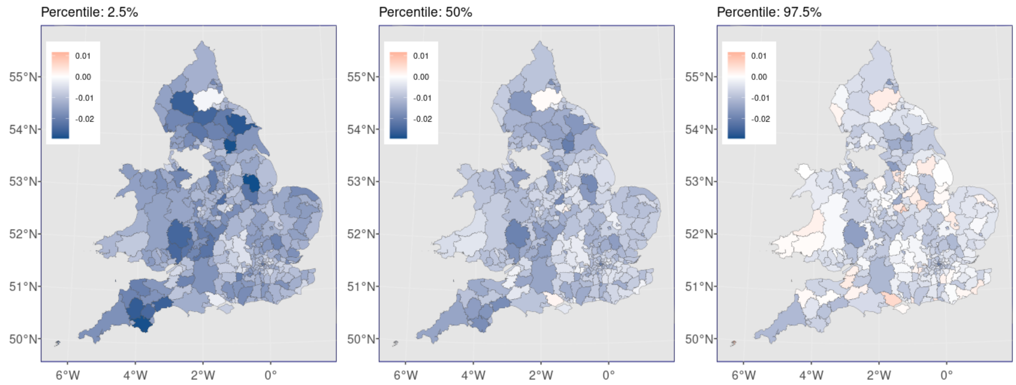
(g) Public order



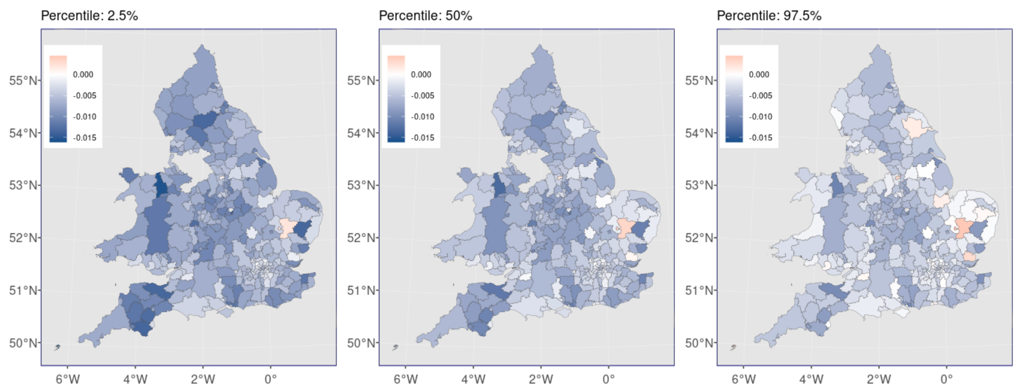
(h) Robbery



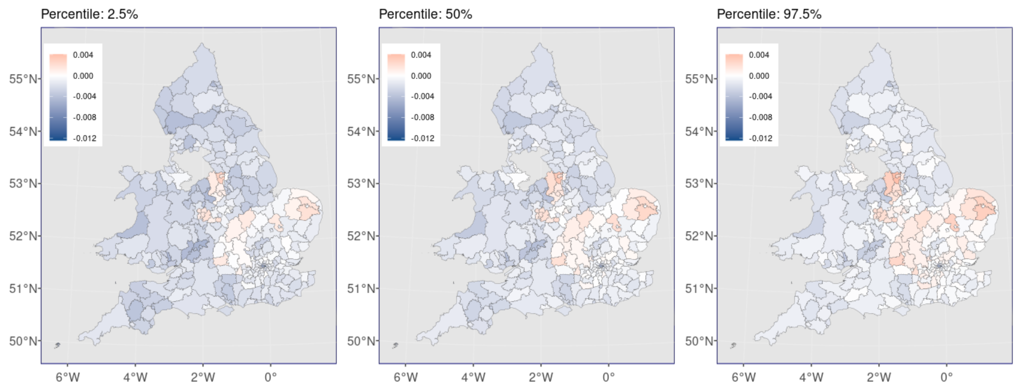
(i) Shoplifting



(j) Theft from the person



(k) Vehicle crime



(l) Violence and sexual offences

Figure 5.5: The effect of SI on different crime types in each local authority is depicted. For each crime type from left to right, the maps are associated with 2.5%, 50% and 97.5% cumulative probability for this effect, respectively. The numbers in the 2.5% and the 97.5% maps indicate the 95% credible interval for effects in each local authority.

were relaxed, both crime types experienced a resurgence, returning to their pre-pandemic levels. Each of these crime categories can be attributed to specific factors contributing to their sharp increases. For instance, the rise in drugs crime can be linked to a shift in law enforcement priorities, whereas the increase in anti-social behaviour crimes can be traced to dissatisfaction among certain individuals with government-imposed measures. The incidence of possession of weapons, public order, violence and sexual offences and criminal damage and arson declined during the pandemic. However, as the pandemic neared its conclusion, there was a resurgence in these offences, with their counts increasing and their trend returning to their pre-pandemic.

In terms of spatial pattern, our model's findings, as illustrated in Figure 5.5, indicate that the impact of the stringency index on anti-social behaviour and drugs crimes remained predominantly positive and consistent across local authorities in England and Wales. Conversely, this impact was predominantly negative and consistent for vehicle crime, burglary, shoplifting, criminal damage and arson, and theft from the person in the study area. For other types of crimes, the effect of the stringency index varied significantly across regions. This signifies that in certain local authorities, the effect was positive, while in others it was negative or insignificant.

This study's findings highlight several key policy implications for maintaining public safety during future health crises. The observed reduction in crimes such as burglary and vehicle theft during strict lockdowns suggests that increased residential occupancy and mobility restrictions can effectively deter these types of criminal activities. Policymakers could consider promoting remote work and strengthening neighborhood security measures in similar situations. The increase in anti-social behavior and drug-related crimes during the pandemic underscores the importance of mental health support and community engagement. Law enforcement must strike a balance between enforcing public health measures and traditional crime prevention strategies, such as neighborhood watch programs, random stop-and-search operations, and foot patrols, to prevent unintended outcomes.

The varying impact of the stringency index across regions highlight the need for tailored, data-driven approaches. Customizing interventions to reflect local demographics and socio-economic conditions can enhance the efficiency and effectiveness of resource allocation. Finally, since some crimes returned to pre-pandemic levels once restrictions were lifted, policymakers should prepare for post-crisis transitions by maintaining specific preventive measures and ensuring clear communication with the public.

There are some limitations to this part of our work. First, we did not explore the underlying causes of the variation observed in the effect of the stringency index across different local authorities and types of crime. Several factors, including population density, demographics, and socio-economic variables, might account for these variations [147]. Future research could utilize data associated with local authorities to examine the contribution of these factors to the spatial variations observed among them. Second, our study is limited by the incomplete data release from the Greater Manchester police force, which prevented us from incorporating data from local authorities within Greater Manchester. Third, our results, which include maps and heatmaps, reflect various events occurring across time and space. We were unable to discuss all of them in detail, but we believe there are interesting patterns that merit further investigation in future work. Lastly, investigating crime evolution at a finer spatial scale, such as the street level, through methods such as point pattern analysis could uncover localized variations and provide a deeper understanding of the crime dynamics before, during, and after the COVID-19 pandemic.

6
Conclusions and Future Work

This thesis has explored the diverse impacts of the COVID-19 pandemic by using advanced statistical approaches, focusing on mortality, CVD risk, and crime trends across different geographical resolutions. Chapters 3, 4, and 5 each address distinct aspects of the pandemic's consequences, employing Bayesian hierarchical models to account for spatial and temporal variations. In this chapter, we revisit the key findings and limitations from these investigations and propose directions for future research to expand this work. Additionally, the results provide actionable insights for public health and policy makers in preparation for future unexpected situations.

6.1 The Effectiveness of Pandemic Mitigation Strategies

6.1.1 Summary, Conclusions, and Policy Recommendations

The effectiveness of COVID-19 mitigation strategies, particularly lockdowns and vaccines, has been the subject of ongoing debate. While public health authorities widely support these interventions as essential in reducing mortality, some critics argue that their impact has been overstated. In the study presented in Chapter 3, we aimed to provide an empirical assessment of the extent to which lockdowns and vaccinations contributed to reducing COVID-19-related mortality in Ireland, while accounting for both regional and temporal variations (In line with Section 1.4). To achieve this, we applied a BHPR model to publicly available mortality data spanning 2016 to 2022. The model works with monthly, county-level mortality data and incorporates a range of explanatory variables: the stringency index, vaccination rates, number of confirmed COVID-19 cases, temperature, and temporal trend. The analysis fulfilled this objective by generating robust, spatially explicit estimate, indicating that approximately 16,876 lives (95% CI: 13,799–20,140) were saved, and by uncovering substantial regional variation in intervention effectiveness. Counterfactual simulations, which estimate the number of deaths that might have occurred in the absence of lockdowns and vaccines, suggest that the most significant reduction in mortality occurred between September 2021 and May 2022. During this period, the difference between predicted (counterfactual) and observed deaths was approximately 2.5-fold, aligning with both the widespread vaccine rollout and the gradual easing of restrictions. While these findings confirm the overall success of lockdowns and vaccinations in saving lives, the impact varied across counties. Dublin, Cork, and Galway experienced the largest reductions in mortality, whereas Cavan and Monaghan saw smaller effects. These regional disparities highlight the importance of evaluating interventions not just at the national level but also locally, as factors such as demographics, healthcare accessibility, and policy implementation can significantly influence outcomes. Although this research is primarily methodological and based on available data, it nonetheless provides valuable insights for the development of healthcare policies in future public health crises. The findings highlight several key considerations:

- Future pandemic responses should incorporate region-specific strategies rather than applying uniform national lockdowns, as effectiveness varies by county.
- Disparities in mortality reductions suggest that investment in local healthcare infrastructure could mitigate pandemic-related deaths more effectively.

6.1.2 Summary of Limitations

Official mortality data from the CSO would provide the most accurate record of deaths; however, it was not feasible for real-time monitoring due to significant delays in the deaths registration process [53]. In Ireland, deaths can take up to three months to be officially registered, and this delay is further extended for cases referred to the Coroner's Court [53]. Given the need for timely mortality data during the COVID-19 pandemic, we relied on `https://rip.ie/` website as a more immediate source. However, this approach carries the risk of undercounting deaths that lack public notices, making county-level estimates less precise, especially during the pandemic when reporting practices and funeral arrangements may have varied.

Additionally, early 2020 case counts rely on a Poisson model with a tenfold multiplier, an assumption not rigorously tested for Ireland's context. Variations in testing availability and strategies could further skew those early estimates. Also, omitting demographic and socio-economic variables such as age structure or income, limits the capacity to explain why Galway outperformed Limerick, for instance. The monthly time interval of data may smooth out short-term shocks and policy shifts that occur on a more granular (e.g., weekly or daily) basis. Finally, since the study ends in August 2022, it does not account for long-term changes in how the virus interacts with the population.

6.1.3 Suggestions for Future Work on the Study Presented in Chapter 3

Future work could take several paths to broaden and deepen these insights. Merging mortality CSO with RIP.ie data could capture an accurate number of deaths. Integrating demographic and socio-economic factors such as healthcare capacity, employment rates, poverty rate, higher education rate and etc. would also help clarify differences in outcomes among counties. Integrating multiple data sources, such as seroprevalence studies and wastewater surveillance, could improve early COVID-19 case estimation by better accounting for under reporting and inconsistencies in testing availability. Additionally, increasing the temporal resolution from monthly to weekly could capture short-term fluctuations and policy effects with greater precision. These refinements would not only provide a more detailed and accurate assessment of pandemic interventions but also strengthen future public health responses by offering a deeper understanding of how policies influence outcomes across different regions and timeframes.

6.2 Long-Term Health Consequences: COVID-19 and Cardiovascular Disease

6.2.1 Summary, Conclusions, and Policy Recommendations

The health impacts of the COVID-19 pandemic extend beyond its immediate respiratory effects, with growing evidence suggesting a potential association between COVID-19 infection and CVD. Given that CVD remains the leading cause of mortality worldwide, assessing whether COVID-19 exacerbates cardiovascular risks, particularly among vulnerable populations, is of great importance. Existing research suggests that the virus may aggravate pre-existing conditions and trigger inflammatory responses that could contribute to long-term cardiovascular complications. However, the magnitude of this effect remains debated, particularly regarding differences across regions and populations. Chapter 4 seeks to quantify the impact of COVID-19 on CVD incidence and examine spatial variations in this relationship across 26 European countries. In this research, we focused specifically on individuals aged 50 and above, as this demographic faces a heightened risk of both severe COVID-19 outcomes and CVD. Aging itself is associated with increased cardiovascular vulnerability due to physiological changes such as vascular stiffening, reduced cardiac function, and a greater prevalence of comorbidities like hypertension and diabetes. Investigating the long-term cardiovascular effects of COVID-19 in this population is crucial for informing healthcare policies and optimizing resource allocation to better support those at highest risk.

To achieve this, we developed a Bayesian hierarchical logistic regression (BHLR) model leveraging data from the SHARE survey. We found that COVID-19 infection increases the odds of developing CVD by 20% (95% CI: 1–44%), with significant heterogeneity across countries. Thus, we successfully met the objectives outlined in Section 1.4. The analysis also identified significant risk factors exacerbating CVD risk post-COVID-19 infection. Hypertension emerged as the most prominent, associated with a 140% increase in odds (95% CI: 117–163%), followed by chronic lung disease (110%, 95% CI: 82–142%), diabetes (35%, 95% CI: 20–52%), and a modest per-unit increase in BMI (1%, 95% CI: 0.4–2%). This study also underscores the importance of spatial modelling in identifying geographical disparities in post-COVID health outcomes, for example, the Czech Republic exhibited a 70% probability of experiencing a higher than average CVD risk increase, while Estonia showed a 28% probability, indicating notable spatial variation. This heterogeneity suggests that country-specific factors, such as healthcare system resilience and pandemic management strategies, may affect the virus's impact on cardiovascular health.

Based on the findings, several policy measures are proposed to mitigate cardiovascular risks in the post-pandemic era:

- Individuals with prior infection, particularly those with comorbidities, should undergo regular cardiovascular assessments to detect early signs of CVD.
- Public health programs should include cardiovascular monitoring into long COVID clinics, ensuring that recovered and vulnerable patients receive appropriate follow-up care.
- Countries with higher CVD risk post-COVID, such as the Czech Republic, should receive additional healthcare resources and funding to address potential surges in cardiovascular complications.
- Public awareness and preventive health campaigns: Given the strong link between pre-existing conditions (e.g., hypertension, diabetes) and post-COVID CVD risk, governments should promote preventive health initiatives focusing on lifestyle modifications, such as diet and exercise.

6.2.2 Summary of Limitations

The reliance on self-reported data in the SHARE dataset introduces potential recall bias and inconsistencies in diagnosis, which may affect the accuracy of the findings. However, these limitations are more likely to lead to an underestimation rather than an overestimation of the observed effects. Additionally, 718 observations were excluded due to missing data, which may have influenced the generalizability of the findings. The relatively small number of infected individuals per country also constrains the statistical precision of the estimates, as reflected in the wide credible intervals. Moreover, as the study focuses on the early stages of the pandemic (2019–2021), it does not capture the true long-term cardiovascular outcomes of COVID-19. Finally, factors such as vaccination status and variations in testing accuracy were not explicitly accounted for, which adds complexity to the interpretation of the results.

6.2.3 Suggestions for Future Work on the Study Presented in Chapter 4

Leveraging SHARE Wave 9 (expected in 2024-25) for longitudinal follow-up would allow for tracking CVD outcomes over five years while also accounting for the effects of vaccination. Expanding the study to include younger cohorts and validating self-reported data with clinical data would enhance both generalizability and accuracy of the results. Furthermore, incorporating contextual factors such as healthcare access, lockdown duration and stringency, living conditions, financial status, and education level could help clarify disparities and inform more targeted interventions.

6.3 Crime Trends During the COVID-19 Pandemic

6.3.1 Summary, Conclusions, and Policy Recommendations

The COVID-19 pandemic led to extensive restrictions, including lockdowns and movement limitations, which significantly altered societal routines. These measures had a profound impact on crime patterns, yet there remains debate on whether these changes were temporary or had lasting effects. In Chapter 5, we focused on examining how crime patterns evolved across England and Wales before, during, and after the pandemic, as well as assess the magnitude impact of restriction policies on different types of crime.

To achieve this objective (1.4), we applied a Bayesian spatiotemporal model to examine the impact of lockdown measures, proxied by the stringency index, on 12 crime types across 339 local authorities in England and Wales from 2015 to 2023. The findings indicate that crime patterns shifted significantly during the pandemic, with distinct trajectories persisting in the post-pandemic period. Burglaries, robberies, and vehicle crimes declined sharply during lockdowns and remained below pre-pandemic levels, likely due to increased home occupancy and enhanced security measures, aligning with RAT theory. In contrast, shoplifting, theft from the person, and violence and sexual offences rebounded to or exceeded pre-pandemic levels as restrictions eased, reflecting restored criminal opportunities and heightened societal stressors, consistent with RAT and GST theories. Anti-social behavior and drug-related crimes surged early in the pandemic, likely due to resistance to restrictions and increased mental health strains, aligning with SAT and GST theories. However, these crimes later stabilized at pre-pandemic levels. Bicycle theft remained largely stable, with a localized increase observed in London. Spatial analysis revealed heterogeneous effects of the stringency index on different crime categories. While it had a positive association with anti-social behavior and drug-related crimes, it negatively impacted burglary and vehicle crime. The effects on other crime types varied, underscoring regional differences in policy responses and socio-economic contexts.

To enhance public safety during future health crises, policymakers should consider several measures based on the findings of this analysis:

- The rise in anti-social behavior and drug offenses suggests a need for mental health support programs, community outreach, and rehabilitation initiatives.
- The sustained decline in burglary and vehicle theft suggests that promoting remote or hybrid work models could indirectly reduce certain crimes by increasing home occupancy.
- Policymakers should ensure that law enforcement agencies can rapidly adapt to shifting crime patterns by adjusting patrols, surveillance, and resource allocation.
- Since some crime rates rebounded while others remained low, continuous monitoring is essential to determine long-term pandemic effects on crime.

6.3.2 Summary of Limitations

Data limitations include the exclusion of Greater Manchester due to missing crime records since July 2019 and incomplete data for Devon and Cornwall post-November 2022, reducing the study's geographical scope and potentially biasing regional comparisons. Additionally, the use of a UK-wide stringency index to measure restriction intensity overlooks regional policy variations within England and Wales, which may have led to misrepresentation of local impacts where restrictions were implemented differently across jurisdictions.

The study's focus on lockdown stringency as a key explanatory variable allowed for a structured assessment of its impact, but we did not explore other underlying drivers of crime trends, such as economic hardship, mental health, or education level. These factors likely played a role in shaping crime patterns alongside pandemic restrictions, and future studies should integrate them to provide a more comprehensive understanding of how various factors interacted during this period. Additionally, while the local authority scale offers a valuable regional perspective, it may mask finer-grained, street-level variations, where crime hotspots or localized socio-economic factors significantly influence trends. A more granular spatial analysis, such as neighborhood-level modelling or point-pattern crime analysis, could yield additional insights into crime dynamics at a micro level.

6.3.3 Suggestions for Future Work on the Study Presented in Chapter 5

Future research could address data gaps by sourcing alternative records and extend beyond May 2023 to assess long-term trends. Region-specific stringency indices or additional covariates (e.g., unemployment, mental health, education) would refine effect estimates. Finer spatial scales (e.g., street-level via point pattern analysis) could reveal localized dynamics, while comparative studies with Scotland or Europe would test generalizability.

6.4 Key Learnings and Reflections

This thesis has shown how spatial and spatiotemporal statistical models, particularly hierarchical frameworks, help us understand geographic patterns and evaluate the impact of factors influencing outcomes in complex public health and societal contexts, with a focus on the COVID-19 pandemic. Several important insights emerged through the process of designing, applying, and interpreting these models. First, a crucial initial step in all the studies presented in this thesis was assessing the availability and quality of public available data. The accessibility of reliable, well-documented, and high-resolution data fundamentally shaped the scope, design, and interpretation of the spatial models developed. In several cases, limitations in data quality or coverage significantly influenced the direction of the research. For instance, in chapter 5, we had to exclude the Greater Manchester area due to missing crime data linked to police IT infrastructure changes. This omission potentially limited the generalisability of our findings and prevented insights into how crime trends in Manchester compared with the rest of the country. Similarly, in chapter 3, analysis of COVID-19 mortality in Ireland, we encountered substantial gaps and inconsistencies in official mortality statistics at the county level. As a result, we used obituary notices from the RIP.ie website as a proxy to estimate all-cause mortality, which allowed for a more complete and spatially resolved analysis. These experiences show how data availability and quality are not only technical concerns but central determinants of research validity, scope, and impact. Second, incorporating spatial information into hierarchical models allows for a more detailed understanding of geographic variation while simultaneously accounting for multi-level data structures. Conventional models that ignore spatial or hierarchical structure often fail to capture dependencies critical for accurate inference and effective policy intervention. Hierarchical spatial models are well-suited to capturing both within- and between-region variation, as well as spatial dependence and contextual effects, thereby revealing patterns that would otherwise remain obscured. Third, the development of interpretable and robust spatial hierarchical models requires careful preparation prior to model fitting. Exploratory spatial data analysis (ESDA) plays a vital role in identifying structure, guiding covariate selection, and diagnosing potential issues such as multicollinearity or data sparsity. Attention must also be paid to spatial resolution, and the nature of spatial autocorrelation, which can influence model performance and interpretation. Finally, interpretability and practical relevance are central to the utility of these models. In addition to assessing statistical performance, it is essential to ensure that models yield clear and actionable insights for decision-makers. This includes effective visualisation of spatial effects, transparent communication of uncertainty, and thoughtful contextualisation within relevant policy or social frameworks.

The methodological lessons and practices developed in this thesis are not limited to pandemic-related studies. They provide a transferable foundation for applying hierarchical spatial models across a wide range of domains, including epidemiology, environmental science, criminology, and socio-economic policy analysis.

6.5 Future Research Directions

The work presented in this thesis opens up several avenues for further investigation, particularly in the application of advanced spatial and statistical modelling to public health and social science domains. Below are three potential directions that could form the foundation of new and substantial research projects:

(1) **Imputation and modelling of Spatial Data with Non-Random Missingness Mechanisms:** A critical methodological gap in the analysis of spatial and spatiotemporal data lies in addressing the presence of Missing Not At Random (MNAR) patterns. In such settings, conventional imputation strategies (e.g., mean imputation, MICE), which rely on Missing At Random (MAR) assumptions, often produce biased estimates particularly in regions or sectors where data are systematically absent due to structural or contextual factors. To overcome this limitation, the research should develop joint modelling frameworks that explicitly account for both the outcome process and the missingness mechanism. Building on selection model approaches, it will explore multivariate extensions of Bayesian Additive Regression Trees (BART), a flexible and nonparametric Bayesian technique capable of capturing complex, non-linear dependencies among observed variables, missingness indicators, and spatial structures. Specifically, two complementary strategies proposed by Goh et al. [111] could be applied:

- Probit-BART Selection Modelling: Jointly modelling the response and the missingness indicator using a multivariate BART for the economic outcomes and a probit regression for the missingness mechanism.
- Dual-BART Modelling: Simultaneously using BART to model both the outcomes and the missingness mechanism (via probit BART), enabling better performance under complex or highly non-linear MNAR patterns.

Once the missing data have been imputed, the completed datasets can then be used for spatial modelling, incorporating geographic contiguity and spatial correlation through conditional autoregressive priors or Gaussian Process layers where appropriate.

Application: There are several possible applications of this type of future research. One such as example is to study regional economic disparities and resilience, with a focus on counterfactual economic scenarios. A key application could be to reassess regional economic trajectories in the absence of recent exogenous shocks, such as the COVID-19 pandemic and the Russia–Ukraine war. Many datasets have large gaps or missing data due to these types of shocks. Using the newly developed spatial imputation tools, this research could provide a robust means of reconstructing more complete economic datasets (e.g., regional gross domestic product, business closure or bankruptcy records, public investment, government aid distribution, purchasing power parity, unemployment and employment rates, industry-specific outputs) where missingness is both non-random and spatially clustered. Subsequently, counterfactual modelling techniques could be used to estimate baseline economic trajectories that could have emerged without these disruptions or shocks. Such analysis could help shed light on the true impact of recent global crises but also revisit longer-term hypotheses about economic cyclicality (e.g., the 8–12 year downturn cycle), asking whether the global economy was structurally poised for a slowdown independent of recent shocks. Ultimately, this research aims to deliver less biased, spatially-aware insights into economic vulnerability and resilience, enabling more grounded forecasts and robust policy planning in the face of incomplete and systematically missing data.

(2) **Developing Non-Stationary Spatiotemporal Point Process Models:** There are opportunities for research involve developing novel statistical methods for modelling the occurrence of point patterns events and their intensity that vary significantly over both space and time, where the spatial relationships (e.g., clustering, inhibition) are not constant and depend on direction (anisotropic). Traditional point process models often assume stationarity or isotropy, which is often unrealistic for complex environmental or health phenomena. The research would involve extending existing spatial point process frameworks (e.g., log-Gaussian Cox processes, Matern cluster processes) to incorporate dynamic, spatially-varying kernels or intensity functions that capture non-stationarity and anisotropy. This would likely involve developing new estimation techniques (e.g., based on MCMC, variational inference, or computationally efficient likelihood approximations).

Application: This research could be applied to developing models to analyze and predict the spatial and temporal patterns of environmentally-triggered health events, such as emergency room visits for asthma exacerbations or acute cardiovascular events, where precise geocoded locations and timestamps of the events are available. The focus would be on understanding how the intensity and clustering of these events relate to highly localized and dynamic environmental exposures, such as air pollution concentrations specifically influenced by air traffic patterns (e.g., under flight routes or near airport operations) or emissions from specific industrial point sources with directional plumes. The non-stationarity of these suggested models is crucial because the impact of air traffic pollution or an industrial plume is not uniform across space; it is concentrated near the source and varies depending on distance, local topography, and meteorological conditions. The spatial clustering of health events is expected to be higher and exhibit different characteristics closer to these sources compared to areas further away. Furthermore, the anisotropy component is vital for capturing the directional nature of exposure and risk. For example, the risk associated with air traffic pollution might be significantly higher directly under flight paths or downwind from runways compared to areas at the same distance but in a different direction. Similarly, the health impact of an industrial emission often follows prevailing wind directions.

(3) **User-Friendly R Package for Facilitating Complex Spatiotemporal Data Analysis Workflows:** Drawing directly from some of the practical challenges encountered during this PhD, such as ensuring data quality, handling missing values, systematic variable and model selection, efficient model fitting, and interpretable visualization for complex spatiotemporal data, research and development work is required to focus on the principles and implementation of developing a comprehensive and user-friendly R package for these workflows. The types of workflows encountered in the work described in this thesis require specialist knowledge of R in addition to skills around data analysis, data management, and so on. So, while making the source code of the work available as open-source software greatly enhances reproducibility, replicability, and accountability, it can still be very challenging for researchers, who are not experts in R and spatiotemporal data analysis, to understand the software and, ultimately, use it.

In work, such as that presented in this thesis, the core work lies not just in coding, but in the research required to design and build a statistical software tool that effectively includes best practices and robust methodologies for common data analysis difficulties encountered in spatiotemporal studies, particularly for users who may not be deep specialists in every underlying statistical technique. To this end, this future research would involve researching and integrating state-of-the-art or otherwise robust methods for automated or semi-automated data quality checks tailored specifically to spatial and temporal data structures. Furthermore, it would necessitate investigating and implementing flexible strategies for handling missing data, including spatially-aware imputation techniques, potentially incorporating the methodologies developed in previous ideas where appropriate. In addition, it would be necessary to explore strategies for guiding users through complex variable and model selection processes in a statistically sound yet intuitive manner. Finally, a significant component would be dedicated to researching efficient computational strategies for fitting complex spatiotemporal models, as well as developing standardized and easily interpretable visualization tools for presenting model outputs and associated uncertainty.

Application: The output of this work would result in a well-documented, open-source R package that provides a streamlined workflow for analyzing hierarchical spatiotemporal data. While applicable broadly, its development would be informed by the specific data types and modeling challenges addressed in the thesis and many more (e.g., health, environmental, economic spatiotemporal data, cell biology [166]). Such a package would serve as a valuable tool for researchers and practitioners in various fields, enabling them to perform sophisticated analyses while abstracting away some of the lower-level complexities, directly contributing to the democratization of advanced data science techniques. The research would include the evaluation the package's performance, usability, and impact on the efficiency and reproducibility of spatiotemporal data analysis workflows.

A

Appendix A

Publication and Author Contributions

This appendix is based on the published article:

> Pourshir Sefidi, N., Mooney, P., Exploring the effects of socioeconomic factors on voter preferences: A case-study of France 2022. *31st Geographical Information Science Research UK (GISRUK) Conference*, (2023). https://doi.org/10.5281/zenodo.7823388

This study was carried out in collaboration with my supervisor; however, I was primarily responsible for conducting the analysis and writing the manuscript. I gathered and preprocessed the French electoral and socio-economic datasets, implemented the Poisson log-linear model with spatial random effects, performed all statistical and spatial analyses, and interpreted the results. My co-author provided supervisory guidance, theoretical input, and editorial suggestions. The version included in this appendix is identical to the published paper, with minor edits for consistency within the thesis.

Summary of Key Contributions

- Developed a Poisson log-linear model with spatial random effects to analyse voting preferences in the 2022 French presidential election.
- Investigated spatial variation in socio-economic determinants of voter preferences at the French department level.
- Identified key socio-economic predictors influencing voting outcomes, including unemployment rate, white-collar rate, poverty rate, and higher education rate.
- Demonstrated that voting behaviour exhibits clear spatial heterogeneity, reflecting the influence of local socio-economic conditions.

- Provided empirical evidence supporting the integration of spatially explicit statistical models in political science research to improve understanding and prediction of election outcomes.

A.1 Introduction

Recognizing the drivers of voter preferences offers clear indications not only for predicting the election's outcome but also for understanding voter behaviours and their influences. Many studies have sought to understand the factors influencing the voting behaviours of citizens [160, 247, 193] with two main approaches emerging. The first approach is to conduct surveys with individual voters and ask them about their preferences and the reasoning behind their choices [119, 36, 193]. This approach is at an individual level, is very time-consuming, and is an expensive process to repeat. Sample size is limited by the budget (financial and time) available. This approach is also limited by the fact that the determinants of voters' preferences vary geographically. The second approach, which utilizes large-scale census data and election results, can overcome these limitations [146, 244, 186]. socio-economic factors that influence voting preferences vary by location [107]. While the identification of these factors has grown over the years, it is incorrect to assume that their spatial distribution is known. Political science researchers have emphasized that these effects should be considered exogenous and unknown. Instead, their spatial distribution should be estimated for each dataset rather than assumed a priori [43, 71, 174]. Darmofal [71] demonstrated spatial variation in the effects of socio-economic factors on voting behaviour during the Democratic realignment period (1928-1936). Miller and Grubesic [186] investigated local halo effects and spatially varying effects of socio-economic factors on Republican support in the 2016 U.S. presidential election.

Many models have been proposed for spatial modelling such as geographically weighted regression [38], Bayesian spatially varying coefficient model [103], Multinomial logit model [84] and Poisson regression model with spatial random effects [26]. In this work, we utilize the Poisson log-linear model as a less computationally expensive alternative to the Multinomial logit model for modelling candidate votes. We aim to investigate how various socio-economic factors impact voters' preferences for the 2022 French presidential election. To our knowledge, this is the first study to use a Poisson log-linear model with spatial random effects to examine the influence of socio-economic factors on voters' preferences for the French presidential election. Our findings reveal that socio-economic factors significantly shape voters' preferences for the French presidential election and that their impact varies spatially.

Table A.1: socio-economic variables and their definition

Variable	Definition
Immigration rate	The percentage of the population classified as immigrants.
Poverty rate	The proportion of individuals considered monetary poor.
Higher education rate	The percentage of individuals over 18 years old with a higher education degree.
Average life expectancy	The average life expectancy of people.
Unemployment rate	Percentage of unemployed people in the total labour force.
White-collar rate	Percentage of population with a white-collar job (i.e., a job that requires a university degree).

A.2 Methodology and Data

A.2.1 Data Description

We investigate the effect of several socio-economic factors (immigration rate, poverty rate, higher education rate, average life expectancy, unemployment rate and white-collar rate) on voters' preferences for the 2022 election at French department [288] level. We utilised three data sources:

- **Election data:** Results of the first round of the 2022 French presidential election. This data consists of 12 candidates and their votes in 96 departments in Metropolitan France.
- **Census data:** Census data is recorded annualy by INSEE (Institut National de la Statistique et des Etudes Economiques). We used either 2019 or 2021 at the department level. A summary of relevant variables and their definition is shown in Table A.1.
- **French department boundaries:** We used an openly available ESRI Shapefile for the French department boundaries.

A.2.2 Modelling Procedure

Candidate votes can be modelled using a Multinomial Logit Model (MLM). Accordingly, $Y_i = \{y_{i1},\ ..., y_{ij},\ ...\}$ is the vector of votes in the department $i\ =\ 1,\ ...,\ I$ and for the candidates $\{j;\ 1\ , \ldots,\ J\}$. We can assume:

$$\mathrm{Y_i} \sim \mathrm{Multinomial}\left(\boldsymbol{\pi}_{\mathrm{i}}\right) \tag{A.1}$$

where $\boldsymbol{\pi}_{\mathrm{i}} = \{\boldsymbol{\pi}_{\mathrm{i1}}, \ldots, \boldsymbol{\pi}_{\mathrm{ij}}, \ldots\}$ is the vector of vote proportions of the candidates. The proportions can then be regressed on the independent variables (e.g., poverty rate). However, as this model specification is computationally expensive we do not use it. Instead, we use Poisson log-linear model that has been shown to be equivalent to MLM [12, 159] and is supported by R-INLA [242] in R for spatial modelling. For more information on MLM see Dow and Endersby [84]. The Poisson log-linear model used here is defined as follows:

$$\begin{aligned} y_{ij} &\sim \mathrm{Poisson}\left(\lambda_{ij}\right) \\ \log\left(\lambda_{ij}\right) &= \phi_i + X_i B_j + s_{ij} \end{aligned} \tag{A.2}$$

where y_{ij} is the number of votes for candidate j in department i, λ_{ij} is the expected number of votes for candidate j in department i, ϕ_i is the intercept for department i, X_i is the vector of covariates for department i, B_j is the vector of coefficients for candidate j, and s_{ij} is the spatial random effect for candidate j in department i. We assume the same structure for all the candidates and drop the "j" subscript for notation simplicity in the following descriptions. We use the Besag model [28] for s_i that is:

$$s_i \mid s_{k \neq i} \sim N\left(\frac{1}{n_i}\sum_{k\sim i} s_i, \frac{\sigma_s^2}{n_i}\right) \tag{A.3}$$

where $k \sim i$ refers to all neighbors of the department i, with n_i representing the total number of neighbors and σ_s^2 is the variance of the spatial random effect.

A.3 Results

With the Poisson transformation used the effect of each predictor on the candidates' votes is not identifiable. However, the difference in the effects is identifiable and we can interpret these differences. From equation A.2, we can calculate the exponentiated difference of coefficients. This indicates the percentage change in the vote ratio for one candidate compared to another. Our analysis focused on how each predictor affected the vote ratio of candidates. As a result, we presented the effects of six predictors: higher education rate, unemployment rate, white-collar rate, poverty rate, immigration rate, and average life expectancy in figure A.1. We focus on Macron, Le Pen, and Melenchon as the primary winners during the first round of the 2022 election.

We report that the vote ratio of Macron to Le Pen decreased by 4.98% for every unit increase in the unemployment rate in a department. This figure is a 5.30% increase for a unit increase in the white-collar rate and a 3.82% decrease for a unit increase in the poverty rate. Effects for higher education rate, immigration rate, and average life expectancy were not significant.

The vote ratio of Melenchon to Macron showed unit increases of 16.63%, 10.80% and 2.23% for higher education rate, poverty rate, and immigration rate respectively. However, this ratio showed a decrease of 8.33%, 1.04% and 3.34% for the unemployment rate, white-collar rate, and average life expectancy in a department.

The vote ratio of Melenchon to Le Pen increased by 13.98% for every unit increase in the higher education rate, 4.20% for a unit increase in the white-collar rate, 6.56% for a unit increase in the poverty rate, and 2.47% for a unit increase in immigration rate. On the other hand, the vote ratio decreased by 12.90% for a unit increase in the unemployment rate and by 2.71% for one year increase in average life expectancy in a department.

Furthermore, the spatial random effects indicate that spatial patterns are not explained by the predictors in our model. Figure A.2 show the map of spatial random effects for Macron and Le Pen. A pattern exists showing overall positive values in the east and negative values in the western parts of France for Le Pen while for Macron positive values are in the north and negative values in the south.

A.4 Conclusions and Future Work

Our study involved developing a model to predict the vote ratio of candidates in the 2022 French presidential election and evaluating how various socio-economic variables influenced voting patterns. We discovered that there were distinct geographic patterns in the way people voted which were tied to different socio-economic factors. Unemployment rate, white-collar rate, poverty rate, and average life expectancy all played a significant role in determining the winner. We also found that higher education rate, unemployment rate, white-collar rate, and poverty rate were all significant factors in determining whether Melenchon would win over Macron and Le Pen. There are several avenues for further exploration in this research. Firstly, we could employ the datasets from the 2012 and 2017 presidential elections to draw comparisons with the 2022 election results. Secondly, we could apply the same model to forecast the vote ratio of candidates in the 2022 election, using data from the 2012 and 2017 elections. Lastly, we could test the effectiveness of our model in other countries to determine whether the findings align with those observed in the French presidential election.

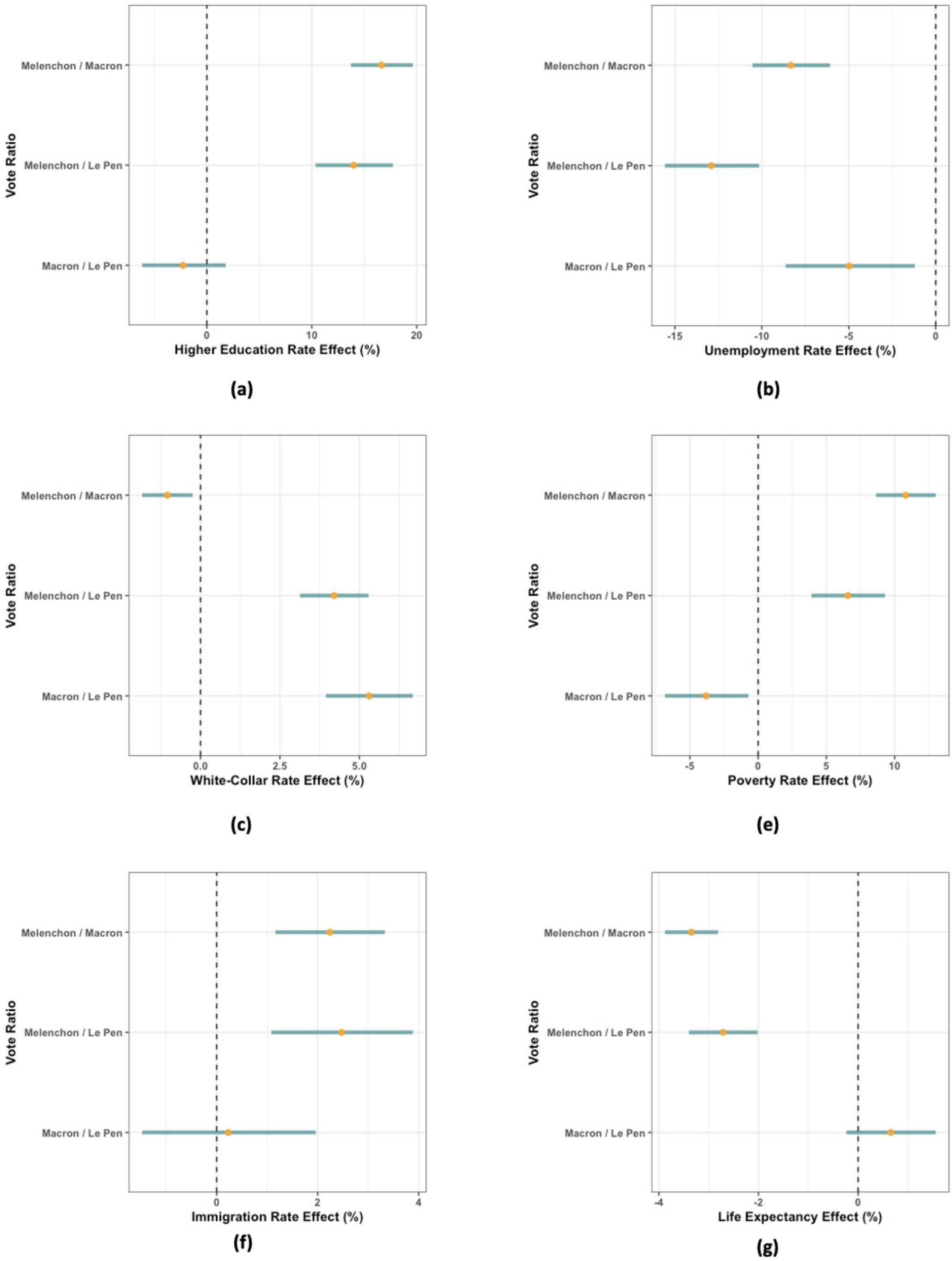


Figure A.1: The effect of each predictor on the percentage changes of vote ratio for candidate i against candidate j is depicted on the x-axis and i/j is shown on the y-axis.

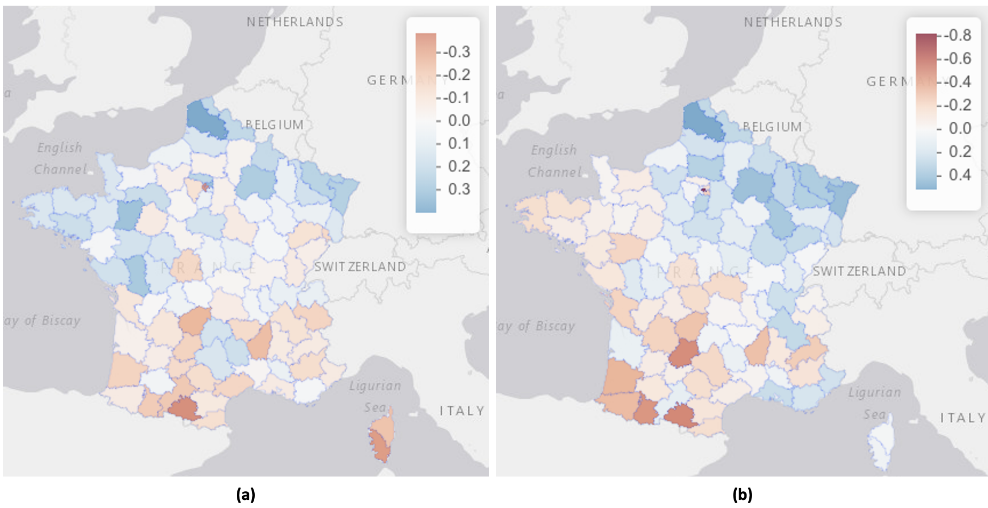


Figure A.2: a) Values of the spatial random effect for Macron b) Values of the spatial random effect for Le Pen, mapped on the French departments.

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