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Mobility patterns of COVID-19 and the impact on the labour market specifically the gender pay gap

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Abstract

This study examines the impact of COVID-19 on global mobility patterns, labour market outcomes, and gender pay disparities across various economic contexts. Using data from Google Mobility Reports and Our World in Data, the analysis employed clustering, correlation, and predictive modelling to assess mobility recovery, economic stability, and gender inequalities. The findings reveal distinct responses between G20 nations and Least Developed Countries (LDCs), with LDCs showing faster mobility recovery due to economic necessity, while G20 nations benefited from remote work infrastructure. Additionally, results indicate that the gender pay gap is likely to persist or widen without targeted interventions, as female-dominated sectors face slower recovery. Recommendations include gender-sensitive hiring practices, flexible work policies, and investment in digital infrastructure to support long-term stability. This research contributes to the understanding of pandemic-related economic impacts and highlights the need for inclusive recovery strategies.

Keywords: COVID-19, mobility patterns, labour market outcomes, gender pay gap, clustering

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1.Introduction and Objectives

1.1 Introduction

In December 2019, a novel coronavirus outbreak, now known as Coronavirus disease 2019 (COVID-19), was first identified in the Hubei province, China. The virus is characterised by its severe respiratory symptoms such as fever, difficulty breathing and cough. The name 'Coronavirus' derives from the Latin word 'Corona' meaning 'crown' (Cascella et al., 2024), which describes the crown-like appearance of the virus. The disease was caused by a SARS-CoV-2 virus, a betacoronavirus belonging to the subgenus Sarbecovirus, a category of coronaviruses that also includes the virus responsible for the 2003 severe acute respiratory syndrome (SARS) outbreak (Ciotti et al., 2020). Coronavirus 2019 shares genetic similarities with the 2003 SARS outbreak, which is why it is also referred to as SARS-CoV-2.

The initial outbreak in Wuhan, China, rapidly spread across neighbouring towns and cities and quickly escalated into a global pandemic. The Chinese government implemented mitigation strategies such as quarantine and social distancing. By January 23, 2020, the city of Wuhan was on complete lockdown (Hu et al., 2021), becoming the first city globally to shut down all forms of travel and transportation. China maintained restrictive measures across the country, with different provinces having varying severity levels. This decisive action significantly reduced new cases within China, showcasing an early, albeit temporary, control over the virus spread. However, while the number of cases started stabilising in China, other parts of the world continued to experience a surge in cases. In fact, over a third of the global population was in some form of lockdown or movement restriction by the middle of 2020 (Koh, 2020). The widespread impact prompted the World Health Organisation (WHO) to officially declare COVID-19 as a global pandemic. Within less than a year of detecting the disease, 216 countries and regions across all continents had more than 20 million cases of COVID-19, with the death toll accumulating to over 733,000 (Hu et al., 2021). Despite global efforts to control the virus, SARS-CoV-2 has continuously mutated and evolved since the first outbreak. New virus variants developed over time, namely Alpha, Beta, Gamma, Delta, and Omicron, causing further difficulty and triggering new waves of pandemic cases while challenging existing restrictive measures.

Fast forward to the present day, it has been over a year since the World Health Organisation (WHO) declared that COVID-19 is no longer a public health emergency of international concern (PHEIC). Yet, the long-term effects of COVID-19 and the implications due to restrictive measures remain evident. The pandemic caused shock waves worldwide, causing one of the largest global economic crises in over a century ("WDR 2022 Chapter 1. Introduction," n.d.). The economic impacts rippled into societies' daily lives, affecting every aspect of human life and redefining how we work, interact and navigate our lives. Many countries are still recovering from the economic recession. For example, the total contribution of travel and tourism to global gross domestic product (GDP) in 2023 was roughly 4% below the year the COVID-19 outbreak occurred ("Travel and tourism," n.d.), highlighting the lasting effects on mobility patterns and the gradual but slow economic recovery within this sector. COVID-19 continues to impact global communities, with the total number of deaths exceeding more than 7 million, highlighting the pandemic's ongoing and lasting effects. As each country imposed restrictions to constrict the spread of the virus, the resultant changes in mobility patterns have had significant implications for public health, the global economy, and labour markets.

1.2 Relevance, Research Gap and Beneficiaries

Relevance

One significant impact of the COVID-19 pandemic was the changes in global mobility patterns. Measures such as national lockdowns, travel restrictions and social distancing were implemented to halt the movement of people and goods within countries and across borders. These policies aimed to prevent disease transmission since close contact with infected people was the most common form of transmission. For several reasons, mobility patterns serve as a critical link between public health measures and economic activity. Firstly, mobility is closely tied to labour markets—workers need to move to access jobs, and the transportation of goods and services is essential for economic output. By early 2020, 43,000 restrictive travel measures were in place, and this number had only more than doubled to 110,000 by the end of 2020 ("The State of Global Mobility in the Aftermath of the COVID-19 Pandemic," 2020). This resulted in a corresponding drop in economic productivity, particularly within industries that relied on in-person activity, such as retail, tourism, and hospitality. For instance, a migration study found that global air travel dropped by 60% in 2020 ("COVID-19 impacts on mobility," n.d.), drastically affecting economies that depend on tourism and international business travel.

Secondly, mobility patterns provide critical data points for monitoring compliance with public health measures and assessing their effectiveness. Mobility data from sources like Google Mobility Reports and Apple Mobility demonstrate how movement patterns changed during lockdowns and throughout different waves of the pandemic, which helped policymakers understand the impact of their measures. For instance, *"Under most conditions, early adoption of non-pharmaceutical interventions is associated with a reduction in transmission"* (Hale et al., 2021). A timely adoption of containment measures is effective in limiting the spread of the virus. However, some studies question the effectiveness of travel restrictions alone, claiming that, in most cases, restrictions were implemented too late to have a substantial impact. ("The State of Global Mobility in the Aftermath of the COVID-19 Pandemic," 2020). This highlights the importance of understanding mobility patterns and how different levels and timings of restrictions influenced the effectiveness of reducing COVID-19 cases.

Mobility patterns also reveal underlying inequalities, particularly in how different populations are affected differently due to pandemic restrictions. A study that assessed the influence of the pandemic on mobility patterns during the first wave found that travel distance and income level were the most influential factors in observing transport users' travel characteristics (Dingil and Esztergár-Kiss, 2021). The results from this study highlighted the spatial-economic inequalities during the pandemic. People with lower incomes who rely on public transport more are at far greater risk and highly exposed to the virus. Amongst all the respondents, 54.1% reported that government-imposed restrictions had restricted their day-to-day activities. This clearly shows the pandemic effects on individual mobility patterns.

Mobility patterns are not just a public health concern but also closely tied to economic output. A study by the International Monetary Fund (IMF) found a strong negative correlation between tighter movement stringency and GDP performance, with a Pearson correlation coefficient of -0.7 between the two variables (Khetan et al., 2022). This highlights the importance of mobility patterns from an economic perspective. *"Human mobility is associated with social interaction and economic development."* (Google.com, 2020). Throughout the pandemic, the world experienced the worst recession since the great depression, with the worst of it by global unemployment reaching 6.5% ("SDG Indicators," n.d.). Economic impacts seemed to have struck less developed countries the most (LDCs), with 43 out of 47 LDCs experiencing a fall in average income (The COVID-19 crisis in LDCs, n.d.). Many of them already faced challenges such as high debt levels, still recovering from the 2008-2009 global crisis, and dependency on sectors such as tourism, which accounted for almost 10% of GDP ("LDC tourism," 2024). The economic crisis spiralled into a global job crisis; within the UK, 1.3 million people lost their jobs as a result of COVID-19 ("Unemployment," n.d.) and a further 11.7 million people furloughed across the UK ("COVID-19 impacts on mobility," n.d.). During this period, the labour market shifted significantly, with remote work being far more prevalent. A survey found that 75.3% of participants reported that they started to work from home after lockdowns (United Nations, 2022). This statistic reflects a fundamental change in the nature of job markets since. Furthermore, businesses had no alternative but to resort to digitalising processes to replace full-time employees. Digitalisation and automation - already feared by many workers - became increasingly widespread and proven successful for many tasks, in fact, much more efficient than humans at a very sustainable cost. "*The pandemic has certainly given employers more reasons to look for ways of substituting machines for workers"* ("The Post-COVID World, Inequality and Automation – IMF F&D," n.d.). The trend was further supported by government funding to ensure businesses were prepared for pandemics and any potential future problems that could affect business operations. In 2021, approximately $10.9 billion was spent on intelligent process automation ("Global spending on automation and AI business operations 2016-2023," n.d.). With the pandemic taking its toll, McKinsey Global Institute found that COVID-19 had accelerated the adoption of automation in nearly 7 out of 10 businesses worldwide (Ventura, 2024), with job sectors that require physical presence, i.e., hospitality, at the greatest risk of digitalisation and automation. Meanwhile, the growth of e-commerce has also been vast and exponential throughout the pandemic, with online transactions surging by nearly 40% globally during 2020 and 2021 ("Global Findex Database 2021 reports increases in financial inclusion around the world during the COVID-19 pandemic," n.d.). This implies a shift in business operations and consumer behaviour. Understanding the dynamics of these mobility shifts is crucial for analysing the broader economic effects that emerged due to the pandemic.

The labour market was significantly affected by the changes in mobility patterns. Women, in particular, were disproportionately affected by these labour market shifts. A study by the McKinsey Global Institute found that women make up 39% of global employment but accounted for 54% of all job losses during the pandemic ("COVID-19 impact on women and gender equality | McKinsey," n.d.). This highlights the challenge women face in the workforce. Existing gender inequality already puts more pressure and vulnerability on women's jobs and livelihoods, and they were nearly twice as likely as men to lose their jobs during the pandemic. This is largely because they are overrepresented in sectors severely impacted by mobility restrictions, such as hospitality, retail, and education, and also due to women taking up more unpaid household and childcare tasks during the pandemic ("The gender gap in employment: What's holding women back? - InfoStories," n.d.). The uncontrolled global pay gap was 0.83 in 2023, meaning women earned 0.83 cents for every dollar men earned. A 0.01 cent increase since COVID-19 began. Similarly, the controlled pay gap stood at 0.99 cents but only increased by 0.02 cents from 2015 ("Global gender pay gap 2023," n.d.). Although there has been an increase in the past, it is still very insignificant and highlights a desperate need for improvement to achieve pay equality. McKinsey's study predicts three possible outcomes by 2030, the worst of which would be to take no action to tackle gender pay inequality. In this instance, the expected global GDP for 2030 would be below where it would have been if COVID-19 affected men and women equally ("COVID-19 impact on women and gender equality | McKinsey," n.d.). The study emphasises the need for targeted efforts to close the gender gap and promote an inclusive economic recovery.

While the pandemic has undeniably impacted global health and economic structures, its effects on the labour market have been particularly significant. As mobility restrictions affected certain sectors more than others, the gendered nature of these sectors became more apparent. Women's labour force participation dropped by over 4.2% in 2020, far more significant compared to the 3% decline for men ("Gender equality, dealt a blow by COVID-19, still has much ground to cover," n.d.). The World Economic Forum 2021 estimates that the pandemic has added an additional 136 years to the time needed to close the global gender pay gap ("It will take another 136 years to close the global gender gap," 2021), further delaying progress towards achieving gender parity. Women who left the workforce due to COVID-19-related mobility restrictions and increased caregiving burdens now face greater challenges in re-entering the labour market (Fletcher et al., 2023). Furthermore, the adaptation of remote work—often seen as a solution to mobility restrictions—has had mixed effects, with some women benefiting from greater flexibility, while others, particularly in lower-income roles, struggled with increased workloads and unclear boundaries between work and home life. These overlapping issues between mobility, labour market participation, and gender pay inequalities highlight the importance of examining these factors together. Focusing on how mobility patterns during the pandemic shaped labour market outcomes, particularly for women. This dissertation aims to contribute valuable insights that can inform future policies to ensure an equitable economic recovery.

Research Gap

Since the start of the pandemic, a considerable amount of research has been conducted on various aspects, including socio-demographic (mobility) and socio-economic factors. Yet significant gaps remain, particularly concerning mobility patterns, labour markets and gender pay disparities. Existing studies have provided valuable insights into the general economic downturn caused by the pandemic, many of which have examined labour market shifts and gender pay disparity as independent issues without looking at how mobility restrictions acted as a critical link between the two. This study aims to build upon existing studies and address the research gaps.

A study which looked into the perceived benefits and harms of COVID-19 (Yao et al., 2023) pointed out that most studies have looked at the immediate impacts of mobility restrictions. Instead, there needs to be more focus on the long-term effects and socio-economic disparity in mobility patterns. "*Exploring and examining the changing trends and patterns of human mobility in both spatial and temporal dimensions are the fundamental analyses in providing an overall picture of mobility changes across space and time*" (Hu et al., 2021). Several studies have looked at mobility patterns throughout COVID-19 in specific regions, revealing how populations move and interact and, as a result, how transmission rates developed. It proved to be an effective way of assessing public health interventions in each study's respective locations. However, hardly any research looked at the changes in mobility patterns before, during, and after the pandemic. Such research could add significant value to our understanding of temporal changes in people's behaviour. It is clear from all research conducted that COVID-19 has had an enormous impact on society, but the extent and finer details remain unclear. In order to obtain a broader understanding of the global context, rather than focusing on one country, it may prove to be valuable to look at the world as a whole. Current studies focus on a specific region/location, and as a result, it becomes difficult to compare the varying economic, political, and healthcare systems that responded to the pandemic. By looking at countries with different strategies, for instance, Sweden's lighter take on tackling Covid 19 compared to China's strict lockdown measures- valuable insights can be gained about the effectiveness of various approaches and allow for a detailed understanding of the trade-offs involved. These comparisons help identify best practices and potential pitfalls that can inform the world in the case of future pandemics.

Mobility patterns are closely linked to economic activity, labour market shifts and overall societal functions, particularly in sectors such as tourism and travel, which heavily depend on the movement of people. The sharp decline in mobility during the pandemic caused global spending in the travel and tourism sector to halve within a year, falling from $6.41 trillion in 2019 to $2.99 trillion in 2020 ("Global travel and tourism spending by type 2022," n.d.). Looking at the trend of economic growth globally is essential to assess the measures implemented and how they fared during the recovery phase. Additionally, it is necessary to look at the long-term impacts on vulnerable populations. Ethnic minority groups, women, young workers and disabled workers have by far been impacted the most ("Health inequalities," n.d.). In the scope of this research, the gender pay gap will be the primary focus. Studies conducted by the International Labour Organisation and McKinsey all show that women faced higher rates of job loss and income reduction than men during the pandemic. However, there is a significant gap in understanding how the gender pay gap has explicitly evolved due to disruptions caused by the pandemic. Most research looks at the immediate impacts on women's employment and wages, but there is a lack of analysis on how these disparities have persisted or changed as economies started to recover. Furthermore, existing studies do not adequately connect the changes in mobility patterns to the widening of the gender pay gap.

The purpose of undertaking this project is to bridge these identified gaps and provide a more comprehensive understanding of how mobility patterns, labour market shifts and gender pay disparities are interlinked and the impact caused by COVID-19. This dissertation aims to fill the identified research gaps and contribute to more targeted policy development for future crises. Understanding these dynamics is not only academically valuable but also essential for informing policies that promote equitable economic recovery, particularly for the most vulnerable populations.

Beneficiaries

Although this research does not directly have any beneficiaries. Several groups may still find the findings within this research beneficial;

1. **Policy Makers and Governments:**

   Insights into mobility patterns, labour market shifts, and gender pay disparity can help policymakers implement data-driven strategies. These can guide targeted support programs. "*Studies have highlighted ways in which gender equality can boost productivity and GDP"* (Kring, 2017)—demonstrating that closing the gender pay gap can improve economic growth by utilising the workforce's full potential.

2. **Researcher and academics:**

   This study aims to fill a critical gap. Academics may find the findings within this study useful or use them as a baseline for further research. According to the publication of Ying Yaon((Yao et al., 2023), the long-term effects of mobility restrictions are an area in which "*further research is urgently needed"*.

3. **Business and employers:**

   Companies will better understand how mobility patterns affect the labour market and, as a result, gender pay disparity within their workforce. This will allow companies to create fairer, more equitable work environments. "*Companies in the top quartile for gender diversity on executive teams were 25 per cent more likely to have above-average profitability than companies in the fourth quartile.*"("Quarterly Promo v1," n.d.) This highlights the benefits businesses can achieve.

4. **General public and workers:**

A better understanding of the pandemic's effect on the labour market may also benefit the general public and workers. This knowledge can help individuals make more informed career decisions and advocate for better working conditions.

1.3 Objectives

To supplement the research gap, the main objectives of this dissertation are as follows:

1. **Analyse mobility patterns changes during the COVID-19 pandemic**

This objective examines how mobility patterns have changed from pre-pandemic to post-pandemic. Its aim is to understand human mobility's spatial and temporal dimensions throughout the pandemic, the underlying causes for this mobility trend and how it affected factors such as case numbers. The goal is to identify trends in reduced or altered movement patterns worldwide.

2. **Examine the impact of mobility restrictions on the labour market and its economic impact.**

This objective assesses how mobility restrictions like lockdowns, travel bans and social distancing measures led to shifts in labour markets across different sectors. It involves analysing data such as unemployment rates and employment trends. This will identify which economies recovered more rapidly and which continued to struggle. This objective aims to understand how different regions adapted to mobility changes and identify which industries faced the most significant labour market challenges while also identifying countries with a strong economic recovery and the possible causation for this.

3. **Investigate the effects of mobility patterns on gender pay disparity.**

Building upon the previous objectives, this objective aims to utilise the findings and analyse how changes in mobility patterns and changes in labour market dynamics affected employment opportunities for men and women. The objective aim is to understand whether gender pay has widened or improved as mobility restrictions were lifted and what potential factors contributed to these trends.

4. **Predict future gender pay trends in the gender pay gap and labour market disparities.**

The final objective involves using predictive modelling techniques to forecast the future trajectory of the gender pay gap by simulating various scenarios, such as different policy interventions, economic recovery rates and shifts in mobility. This will provide insights into potential outcomes and the most effective strategies for reducing gender inequalities in the workforce. Based on these findings, targeted policy measures can be developed.

1.4 Methods

This section outlines the approaches to be used to achieve this study's objectives. Throughout the research, a combination of qualitative and quantitative methods will be used.

1. **Analysing mobility patterns changes**

To analyse mobility patterns from pre-pandemic to post-pandemic periods, this study will utilise secondary data analysis. Mobility data will be collected from sources, namely Google mobility reports, which provide various data regarding movement trends worldwide. Descriptive statistics will be carried out to give a preliminary understanding of the spatial and temporal context of changes in mobility. Geospatial analysis and time series analysis will be conducted to identify key trends and patterns, and clustering can be used to group regions and countries with similar mobility patterns. Python software will be used to create data visualisations and analyse patterns. These findings will be cross-referenced with different sources and studies to ensure the validity and reliability of the results.

2. **Examining the relationship between mobility restrictions, labour market and economic measures**

Labour market data will be collected, and data such as unemployment rates, employment by sector and economic growth indicators such as GDP will obtained. In this instance, rather than analysing every country, a selection of countries and continents will be examined to provide a representative sample. Regression analysis will be used to assess the relationship between mobility restrictions and labour market shifts, and these results will be compared with those of the selected regions to identify differences and commonalities in economic outcomes.

3. **Investigating effects of mobility patterns on gender pay disparity**

Regression and correlation analysis will be used to assess the impact of mobility changes on gender-based employment outcomes. Clustering will also be used to understand how different groups were affected by shifts in mobility.

4. **Predicting future trends in gender pay gap and labour market disparities**

Using machine learning algorithms, scenario-based modelling will simulate different future scenarios, including varying economic recovery trajections and mobility shifts. Based on these findings, targeted policy recommendations will be developed.

1.5 Workplan

The work plan below *figure(1)* outlines the plans to fulfil this study. It is designed to address the objectives and ensure a comprehensive analysis of the study. An initial literature review was conducted to identify the research gaps, followed by data collection and cleaning from various sources. The data analysis stage will employ various techniques, including descriptive statistics, geospatial analysis, clustering and regression analysis. Subsequently, machine learning modelling will be used to predict future trends. The effectiveness of machine learning models will be statistically evaluated. Finally, the insights obtained will be compiled into a report, and policy recommendations will be formulated to provide targeted strategies for addressing the identified issues, ensuring the findings contribute meaningfully to academic and practical applications.

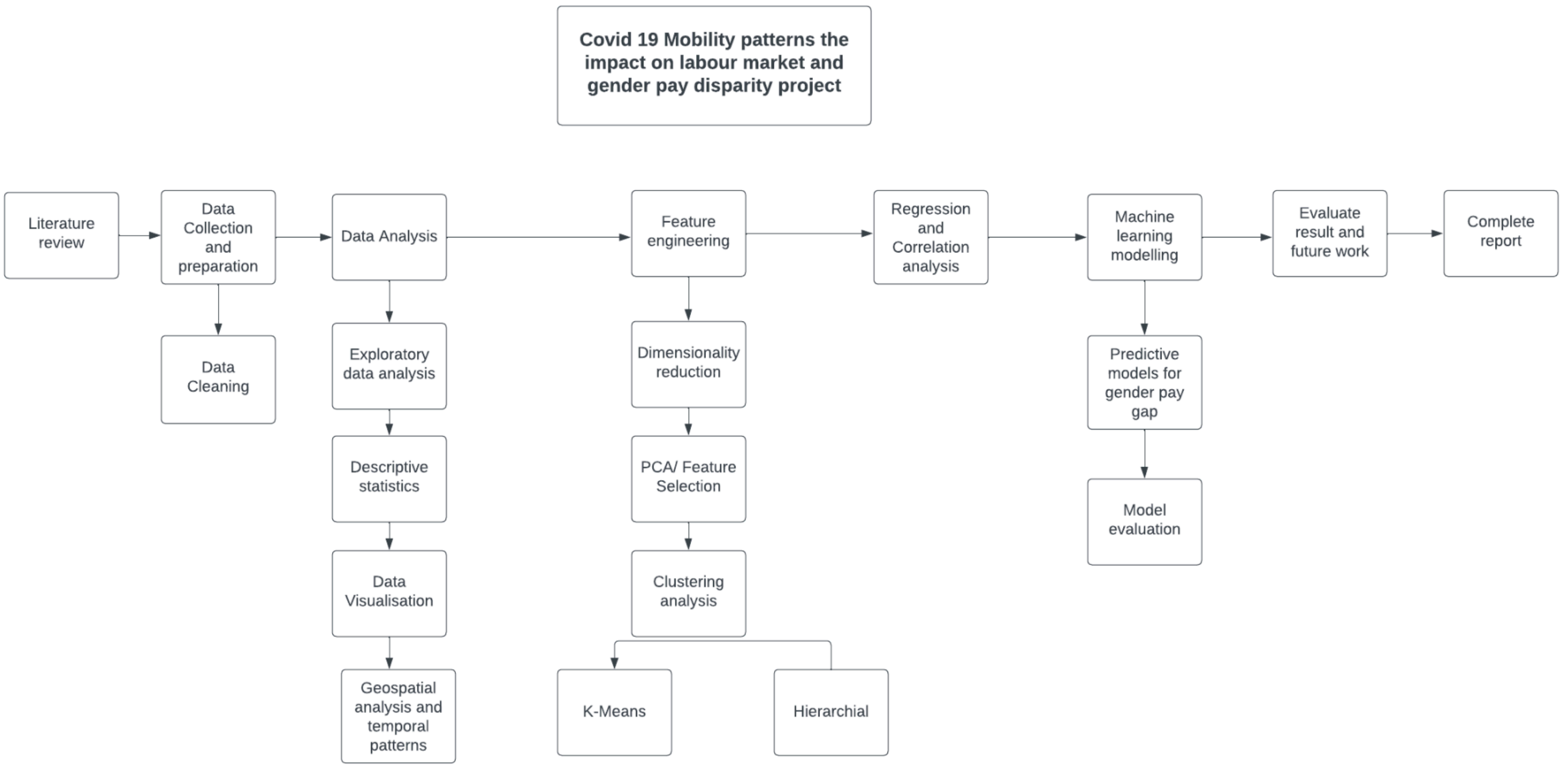


Figure (1): Flowchart showing work plan for dissertation

1.6 Changes in goals and methods

- The analysis utilised the Prophet model for predicting the global gender pay gap, focusing on controlled and uncontrolled scenarios while incorporating mobility, GDP, and unemployment. Instead of a final linear regression model, Prophet was employed due to its effectiveness in handling seasonal trends and complex relationships within the data. Various rates were established for different scenarios.

1.7 Structure of the report

The structure of the report is as follows;

Section 1 - Introduction and Objectives, provides an overview of the study's background, outlining the problem statement, detailing the research objectives, and highlighting the relevance and purpose of the study.

Section 2- Context provides the necessary background information and reviews relevant literature using previous studies to frame the analysis presented later in this study.

Section 3 - Methods, outlines the data collection, analytical techniques and visualisations employed to achieve the study's objectives, giving an in-depth description of how each stage of the research was carried out.

Section 4 - Results present key findings, highlight mobility trends, and analyse the relationship between mobility and economic measures and the outcomes of predictive models. It provides a comprehensive view of the results in relation to the research objectives.

Section 5 - Discussion interprets these results, reflecting on the methods used and referring back to the goals put in place for this study.

Section 6 - Evaluation, reflections, and conclusions evaluate the study overall, reflecting on the methods used. This section also includes challenges encountered and how they were addressed, as well as the scope for future work.

There is also a glossary section that provides definitions of key terms used throughout the study.

The references list all the academic reports, papers, data sources, and any other materials cited throughout the report, following the Harvard referencing style.

The appendix section includes all supplementary materials that support the main content of the report.

2. Context

Introduction

This chapter aims to provide a clear understanding of the research by looking at what is currently known about mobility patterns during the COVID-19 pandemic, the economic effects of these changes, and how they relate to gender pay gaps.

By reviewing various studies and literature, this chapter will highlight important gaps in the existing research that need further investigation. This will help show why it is essential to understand changes in mobility, as they play a crucial role in addressing gender pay disparities.

2.1 Current State of Knowledge

Mobility Patterns During the Pandemic

Research indicates that mobility declined sharply during the initial phases of the pandemic. A study by Abu-Rayash and Dincer (2020) reported a marked decrease in driving by as much as 50%, alongside significant reductions in transit usage, as many countries enforced lockdowns. Specifically, full lockdowns were found to decrease overall mobility by nearly 25% within just a week, illustrating the immediate effects of these measures on daily life. In contrast, lifting restrictions led to an increase in mobility of almost 18% during the same period (de Palma et al., 2022), indicating that government policies directly influenced public movement patterns. This profound impact on daily mobility highlights the importance of understanding how such restrictions altered not only transportation habits but also social interactions and lifestyle changes during the pandemic. The analysis of mobility patterns alongside COVID-19 cases in a region by region case could prevent the need for complete lockdowns.

Several studies have conducted in-depth analyses of mobility patterns to understand the effects of COVID-19 better. For instance, the study of (Kartal et al., 2021) utilised mobility data from mobile applications, namely Google Mobility and Apple Mobility, to analyse changes in human behaviour during the pandemic. They found significant decreases in travel, particularly in urban areas, and emphasised the importance of using technology for real-time data collection to inform public health responses. The study looks at the evolution of mobility during the pandemic, specifically in Turkey, as a form of mobility analysis. Similarly, a study by (Roelofs et al., 2022) investigated the spatial-temporal patterns of mobility during COVID-19 by examining geolocation data in the Netherlands. The research highlighted how mobility varied by demographic factors, noting that vulnerable populations experienced more significant mobility reductions, which added to existing inequalities. It also concluded that spatial mobility patterns should be a key determinant in exploring regional mobility restrictions as an alternative to nationwide lockdowns.

Another study by (Ilin et al., 2021) aimed to prove that publicly available data such as Google mobility data - can be used to evaluate the effectiveness of non-pharmaceutical interventions. Analysing the correlation between mobility patterns and COVID-19 case numbers across different regions with the use of geospatial temporal trends. It utilised various datasets to capture different variables for a broader analysis. The study concluded that understanding mobility trends is crucial for predicting infection rates and formulating effective containment strategies. A particularly interesting finding from this study was the fact that a form of non-pharmaceutical intervention policy during COVID-19 was associated with a decrease in mobility by 81%.

These studies collectively emphasise the profound impact of government restrictions on daily movement and highlight the critical need for comprehensive analyses of mobility patterns. Researchers can provide valuable insights that inform future public health policies and interventions aimed at promoting equitable recovery in the wake of the pandemic. The study of (Sulyok and Walker, 2020), which looked at Google mobility reports and analysed mobility, highlighted the need to figure out the *'underlying patterns observed in mobility*' by looking at the factors for why mobility behaved a certain way during a specific time period gives a better understanding of mobility patterns. Furthermore, the study also encourages future studies to conduct comparisons of individual countries' correlation, specifically economic development status.

Economic Implications

The restrictions on movement during the COVID-19 pandemic had a profound impact on economic productivity. The World Bank reported a global economic contraction of 4.3% in 2020, with sectors heavily reliant on in-person interactions, such as tourism and hospitality, experiencing particularly severe downturns ("Global Economy to Expand by 4% in 2021; Vaccine Deployment and Investment Key to Sustaining the Recovery," n.d.). This relationship between mobility restrictions and economic performance is further substantiated by findings from the World Development Report (WDR 2022), which identified a significant correlation between the stringency of lockdown measures and declines in GDP across various countries. The study of Sulyok and Walker (2020) emphasises that examining GDP data in relation to mobility patterns offers valuable insights into the intertwined nature of these two factors, highlighting the need for a comprehensive analysis of how mobility influences economic stability.

In parallel, changes in mobility patterns directly influenced labour market outcomes. The study by Caselli et al. (2022) investigated the effects of COVID-19-related mobility reductions on local labour markets in Italy. They found that decreased consumer foot traffic led to significant revenue losses for many local enterprises, resulting in widespread job losses and furloughs for workers. Their research emphasised the necessity for targeted economic support measures to assist businesses and safeguard jobs during periods of restricted mobility. They noted that unanticipated local restrictions on individuals were effective tools for containing the circulation of people while also managing the spread of the virus but warned that implementations of lockdowns may have caused a prolonged adjustment period for the labour market to reach a new equilibrium.

The article “Health Inequalities” (n.d.) highlights that ethnic minority groups, women, young people, and individuals with disabilities were disproportionately affected economically by the pandemic in the UK. This finding is supported by Bulteau et al. (2023), who examined the gendered impacts of mobility during the lockdown in France. The study revealed that women exhibited significantly lower mobility than men, often travelling less for work and leisure. Further analysis involved looking into how various factors, including caregiving responsibilities and occupational roles, contributed to these mobility disparities. The research indicated that women, who traditionally assume a larger share of household and caregiving duties, faced additional constraints limiting their ability to travel, compounding job losses among women during the pandemic.

Together, these studies highlight the broader implications of mobility restrictions during the pandemic, illustrating not only the inequalities in health outcomes but also the socioeconomic factors that increase these disparities. Understanding how mobility patterns differ by gender and other demographic factors is crucial for developing targeted policies that address these inequalities and promote a more equitable recovery in the aftermath of the pandemic.

Furceri et al. (2022) suggest that future research should examine the stringency of containment measures and policy responses to better understand labour market inequalities.

Gender Pay Gaps and Labor Market Dynamics

The pandemic's effects on mobility also revealed significant disparities in the labour market, particularly concerning gender pay gaps. Women were disproportionately affected by these labour market shifts, with many employed in sectors severely impacted by mobility restrictions. According to a report by the International Labour Organization (ILO), there were 13 million fewer women represented in employment in 2021, highlighting the existing vulnerabilities in the workforce ("Fewer women than men will regain employment during the COVID-19 recovery says ILO | International Labour Organization," 2021). This has significant implications for the gender pay gap, which, as reported by (Profeta, 2021), the pandemic has further aggravated pre-existing gender gaps, causing a 'she-cession.'

Several studies have investigated the intersection of mobility, employment, and gender disparities during this period. For instance, a study by Alon et al. (2021) analysed how lockdowns disproportionately affected women in various sectors, particularly in roles that require physical presence, such as retail and hospitality. They found that the mobility restrictions not only led to higher job losses among women but also hindered their ability to return to work as lockdowns were lifted (Alon et al., 2020). This study highlighted the urgent need for policies that specifically target the reintegration of women into the workforce as economies recover.

Understanding these dynamics is crucial for identifying strategies to address gender pay disparities. As economies recover, it is essential to analyse how changes in mobility patterns may influence job opportunities and wage structures differently for men and women. This study will build on these findings by exploring the long-term effects of mobility restrictions on gender pay gaps and labour market dynamics across different regions. By examining how varying levels of mobility and economic policies have impacted employment opportunities for men and women, this research aims to provide insights that can guide policymakers in developing effective strategies for fostering gender equity in the workforce during the recovery phase and beyond.

2.3 Analysis Methods

Clustering Analysis: K-means and Hierarchical Clustering

Clustering analysis, including K-means and hierarchical clustering, has been employed to investigate mobility patterns and their impact on economic and labour market outcomes during the COVID-19 pandemic. For instance, (Venkatesh et al., 2022) utilised K-means clustering to categorise countries based on mobility similarity and COVID-19 case numbers. The study identified distinct clusters that showed varying degrees of mobility restrictions and infection rates, providing insights into how different regions adapted to the pandemic. The elbow method was used to derive the chosen number of clusters. The findings emphasised the importance of tailoring public health responses to regional mobility patterns, demonstrating that a one-size-fits-all approach may not be effective.

Similarly, the study by (Ayan et al., 2021) employed hierarchical clustering to analyse mobility patterns across different demographic groups in Rio de Janeiro, Brazil. The research compared different clustering techniques and found agglomerative (hierarchical clustering) and k- k-means significantly outperformed traditional clustering techniques. The research found that areas with high mobility locations within communities and localities can be used by local authorities to implement measures using clustering. The study highlighted the critical role of understanding demographic factors when analysing the impact of mobility changes.

In addition, a study by (Elarde et al., 2021) utilised clustering techniques to explore how urban and suburban mobility patterns changed during the pandemic in the USA. The research applied K-means clustering to segment communities based on mobility trends derived from mobile phone data. It was discovered that certain demographic and socioeconomic factors significantly influenced mobility patterns, revealing that disadvantaged communities experienced more substantial mobility reductions. This study not only underscores the relevance of clustering analysis in identifying distinct mobility trends but also highlights the implications for targeted public health interventions and support measures for vulnerable populations.

By employing both K-means and hierarchical clustering in a visually interpretable way, such as choropleth maps and dendograms, along with insights from studies, researchers can gain a deeper understanding of how mobility changes are associated with labour market outcomes and gender pay gaps, paving the way for more tailored policy interventions.

Time Series Analysis

In addition to clustering techniques, time series analysis has emerged as a crucial method for examining how mobility patterns evolved over time during the COVID-19 pandemic. For instance, Zeng et al. (2021) applied time series analysis to assess changes in urban and suburban mobility in South Carolina, USA. The primary goal of their study was to inform proactive approaches to non-pharmaceutical interventions and to predict future COVID-19 case numbers based on mobility trends.

The study successfully validated its hypothesis that population mobility is associated with COVID-19 transmission. Additionally, it achieved accurate predictions of COVID-19 case fluctuations in relation to changes in mobility patterns over different periods. Zeng et al. (2021) advocate for future research to assess mobility over time across different locations, suggesting that such cross-comparative studies could yield more insights into COVID-19 transmission dynamics. The study also recommends accounting for time-varying factors such as seasonality and weather conditions in future studies.

Time series analysis offers valuable insights into the temporal dynamics of mobility data by examining how mobility, economic indicators, and gender pay gaps have changed over time using current data. While also enabling the forecast of future mobility trends based on historical patterns. By employing methods such as linear regression, the underlying factors influencing changes in mobility, including economic activity, public health guidelines, and shifts in social behaviour, can be analysed. This method is particularly useful for understanding how mobility patterns correlate with labour market indicators.

The integration of time series analysis with clustering techniques enriches the scope of the study, allowing for a comprehensive understanding of how various factors influence mobility patterns over time. This dual approach can provide valuable insights into the long-term impacts of mobility restrictions on economic recovery and labour market dynamics, ultimately guiding more effective policy interventions.

Linear Regression for Predictive Modeling

Linear regression has emerged as a key method for understanding the relationships between mobility patterns and labour market dynamics, particularly during the COVID-19 pandemic. A study by (Chakraborty et al., 2022) utilised linear regression techniques to model the effects of mobility restrictions on employment levels across various sectors in the United States. The analysis revealed interesting findings, such as an increase in working from home, which also led to an increase in daily trips outside during the pandemic. This study emphasises the need for predictive models that integrate mobility data to inform effective policy measures aimed at economic recovery.

Similarly, the research by (Cartenì et al., 2020) focused on the impact of mobility on the COVID-19 pandemic in Italy. Employed multiple linear regression models to analyse the impact of mobility restrictions on various socio-economic indicators in Italy during the COVID-19 pandemic. By integrating data on mobility patterns, economic activity, and health outcomes, the researchers aimed to quantify the direct and indirect effects of lockdown measures. The multiple linear regression approach allowed the authors to assess how changes in mobility influenced factors such as economic performance, healthcare utilisation, and social behaviour while controlling for potential confounding variables. This approach provided a comprehensive understanding of the complex relationships between mobility restrictions and socio-economic outcomes. The findings highlighted that mobility reductions were associated with significant declines in economic activity and alterations in social interactions. The study emphasised the importance of considering mobility data in policy-making to balance public health objectives with economic and social considerations. This research underscores the utility of multiple linear regression models in evaluating the multifaceted impacts of mobility restrictions, offering valuable insights for future policy decisions.

Building on these findings, this study will utilise linear regression to further explore the relationship between mobility patterns, COVID cases, and economic indicators such as unemployment and the gender pay gap. By examining the interplay of these factors, the research aims to provide insights that can inform targeted policy interventions and contribute to a more equitable recovery in the post-pandemic and for potential future global pandemics.

3. Methods

3.1 Overview

This section describes the approach used to achieve the study's objectives. The study used a mix of quantitative and qualitative methods, using several datasets to analyse the focal aspects of the research: mobility patterns, labour market changes, and gender pay gaps.

3.2 Data Collection and Handling - Google Mobility reports

To assess mobility patterns during COVID-19, The Google Mobility Reports dataset was obtained from Google Mobility reports ("COVID-19 Community Mobility Report," n.d.). The dataset would provide a preliminary analysis of mobility reports across various categories compared to a baseline value pre-COVID. Baseline values represent the typical standard value for that day. The dataset spans from 15 February 2020 until 15 October 2022. The Google Mobility Reports dataset is valuable for studying mobility patterns for several reasons;

1. Covers the globe - the dataset has global coverage, making it suitable for country/continent comparison
2. Public and easily accessible
3. Covers a wide range of sectors such as workplaces, retail and recreation
4. Anonymous - Since the data is anonymous, it maintains user privacy.

However, there are also some limitations to using Google's mobility data. The data only includes users who have enabled location history on their smartphone devices, potentially causing a selection bias. This could disproportionately reflect mobility patterns of higher-income individuals or populations with greater access to smartphones, which may not accurately represent the movement behaviour of the entire population (Deng et al., 2024). This is quite significant when considering the number of people worldwide who own a smartphone - " *some 4.3 billion people - now own a smartphone"* (cgill@gsma.com, 2023). However, this limitation is unlikely to significantly affect the overall findings in this study as this analysis focuses on broader, global trends rather than individual-level behaviour. Furthermore, as the research progresses, more datasets will be incorporated, which will help balance out the bias in Google's mobility data.

Upon importing the dataset. The dataset contains data from 135 countries with a total of 11,730,025 rows and 15 columns. A summary of the data frame was created to analyse the data types, as shown below.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11730025 entries, 0 to 11730024
Data columns (total 15 columns):
 #   Column                                              Dtype
---  ------                                              -----
 0   country_region_code                                 object
 1   country_region                                      object
 2   sub_region_1                                        object
 3   sub_region_2                                        object
 4   metro_area                                          object
 5   iso_3166_2_code                                     object
 6   census_fips_code                                    float64
 7   place_id                                            object
 8   date                                                object
 9   retail_and_recreation_percent_change_from_baseline  float64
 10  grocery_and_pharmacy_percent_change_from_baseline   float64
 11  parks_percent_change_from_baseline                  float64
 12  transit_stations_percent_change_from_baseline       float64
 13  workplaces_percent_change_from_baseline             float64
 14  residential_percent_change_from_baseline            float64
dtypes: float64(7), object(8)
memory usage: 1.3+ GB
```

Figure(2) List of variables and corresponding data types of the Google mobility reports

The data structures were all correctly formatted except for the date column, which was stored as an object. This was changed to a date-time format. The reason for the change was it would enable a time-based analysis later on.

A copy of the original data frame was made to make changes without affecting the original dataset. Several columns, such as 'sub_region_1' and 'sub_region_2', were dropped from the dataset as they were not deemed necessary and allowed the data to be more concise. The primary columns required for this study were:

- '*Retail_and_recreation_percent_change_from_baseline*' - Contains mobility trends for public places such as restaurants, shopping centres, theme parks, etc
- '*grocery_and_pharmacy_percent_change_from_baseline*' - Contains mobility trends for grocery shops, drugstores and pharmacies.
- '*park_percentage_change_from_baseline*' - Contains mobility trends for national parks and local parks.
- '*transit_stations_percentage_change_from_baseline*' - Contains mobility trends for public transport hubs, such as stations.

- ‘*workplace_percentage_change_from_baseline*’ - Contains mobility trends for workplaces.
- ‘*residential_percentage_change_from_baseline*’. - Contains mobility trends for places of residence.

The dataset contained a substantial number of missing values, as shown in *Figure (2)*.

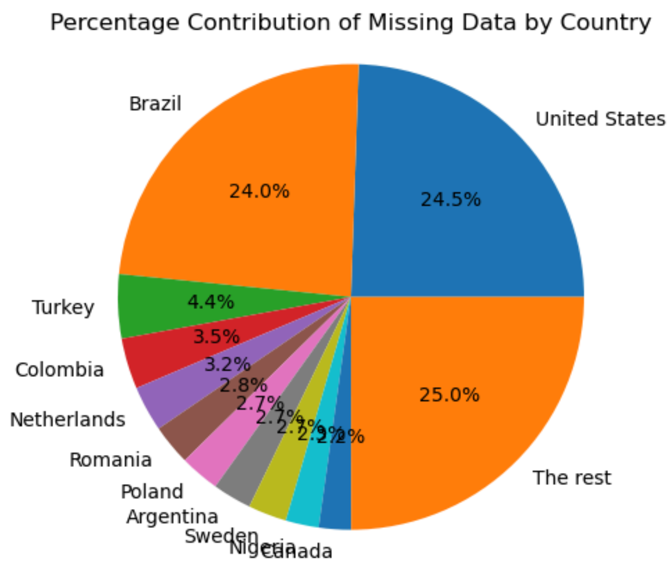
```
country_region_code                                      7244
country_region                                              0
date                                                        0
retail_and_recreation_percent_change_from_baseline    4466484
grocery_and_pharmacy_percent_change_from_baseline     4809378
parks_percent_change_from_baseline                    6236774
transit_stations_percent_change_from_baseline         5923240
workplaces_percent_change_from_baseline                411782
residential_percent_change_from_baseline              4483912
dtype: int64
```

Figure(3) shows the number of missing values for every column Google Mobility reports

To interpret the missing values better, the missing values were grouped by the ‘country_region’ column and the total number of missing data points for each country was calculated. To ensure the visual representation of missing data was clear, countries that contributed less than 2% to the total missing data were grouped into an ‘other’ category. The formula used for this calculation was

$$percentage\ contributions\ (country)\ =\ \frac{Number\ of\ missing\ values\ (\ country)}{Total\ number\ of\ missing\ values}\ x\ 100$$

The final decision was to leave the data untouched because inputting values could introduce bias or distort the trends. A significant portion of the missing data came from the United States and Brazil. Since the analysis focuses on broader trends, the missing data would not significantly affect the overall conclusions of this study.



Figure(4): Pie chart of percentage of missing values by country

3.3 Exploratory Data Analysis

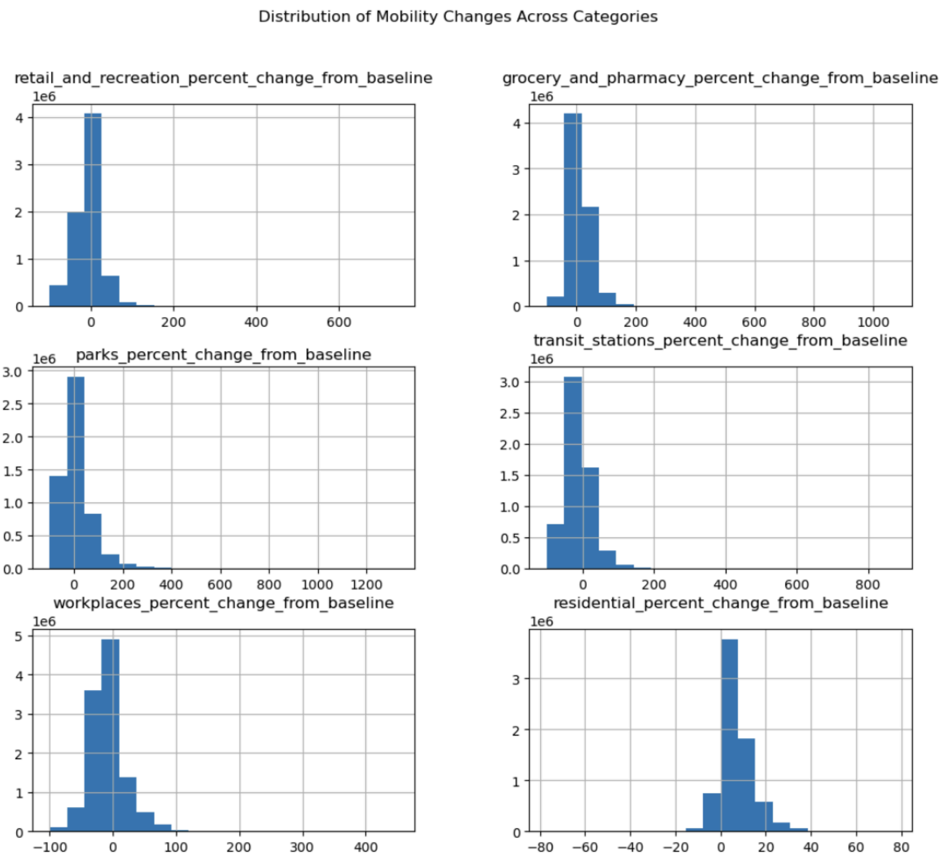
Exploratory data analysis (EDA) was conducted to understand the structure of the mobility data, uncover patterns, and prepare the dataset for further analysis. This is essential for finding instant trends, detecting anomalies, and setting the foundation for methods deployed later in this study. EDA is fundamental research conducted by data scientists to make judgements and develop hypotheses by describing the important relationships and properties within a dataset ("Importance and Impact of EDA in Data Science—DZone," n.d.).

The first step involved calculating descriptive statistics for the variables using the Python built-in function describe(). Descriptive statistics provide an overview of the data by summarising measures like the mean and standard deviation, which are essential for understanding central tendencies, variance, and distribution (Bhandari, 2022). For example, *parks_percentage_change_from_baseline* and *transit_stations_percentage_change_from_baseline* had relatively high standard deviations, suggesting that mobility patterns varied significantly between countries for these factors. In contrast, *residential_percentage_change_from_baseline* had a much smaller standard deviation, implying more consistent patterns and less variation. Many of the mobility variables also had a minimum of -100, indicating that in certain places, mobility dropped to 0.

	count	mean	std	min	25%	50%	75%	max
census_fips_code	2521306.0	31361.354540	16404.970898	1001.0	18141.0	29187.0	47007.0	72151.0
retail_and_recreation_percent_change_from_baseline	7263541.0	-6.672587	31.333509	-100.0	-23.0	-6.0	9.0	741.0
grocery_and_pharmacy_percent_change_from_baseline	6920647.0	14.610500	35.566731	-100.0	-4.0	9.0	29.0	1071.0
parks_percent_change_from_baseline	5493251.0	10.947673	66.151308	-100.0	-29.0	-1.0	34.0	1327.0
transit_stations_percent_change_from_baseline	5806785.0	-11.874881	39.277844	-100.0	-37.0	-16.0	7.0	874.0
workplaces_percent_change_from_baseline	11318243.0	-8.774174	27.653382	-100.0	-25.0	-12.0	3.0	450.0
residential_percent_change_from_baseline	7246113.0	6.674981	7.378810	-77.0	2.0	5.0	10.0	77.0

Figure(5): Table showing descriptive for Google mobility reports

Next, the distribution of mobility changes was explored using histograms. This helped visualise the spread of mobility changes and detect skewness amongst the distributions, indicating whether the data was symmetrically distributed or had outliers.



Figure(6): distribution histogram of mobility variables

All mobility variables exhibit mainly around 0, suggesting most mobility changes were near baseline levels. Some mobility variables have a larger scale than others. For instance, the range for park percentage change exceeds 200. Furthermore, for all mobility variables, there is greater representation on the negative scale except for residential mobility.

A correlation analysis was conducted, too, to assess the relationship between different mobility variables. Correlations were calculated using the Pearson correlation coefficient, which measures linear relationships between two variables (Turney, 2022).

$$r = \frac{\Sigma(x_i - [\bar{x}])(y_i - [\bar{y}])}{\sqrt{\Sigma(x_i - [\bar{x}])^2 \Sigma(y_i - [\bar{y}])^2}}$$ (Turney, 2022)

Where:

- r is the Pearson correlation coefficient
- x_i And y_i are the datapoints
- $[\bar{x}]$ and $[\bar{y}]$ are the mean of the data

Although this calculation was computed through Python's function, it iterated through every two variables and captured how changes in the two variables were tracked from the first data to the final. A coefficient closer to 1 indicated a strong positive correlation, and -1 suggests a strong negative correlation. Correlation analysis is a commonly used analysis method to understand how different sectors influenced one another during the pandemic. However, it must be noted that correlation does not imply causation; while some variables may move together, this does not mean that one makes the other change. Furthermore, the correlation here does not account for time-series trends. The resultant was a grid heatmap displaying the Pearson correlation coefficient, where dark red shaded cells indicate stronger positive relations and contrastingly dark blue suggests a stronger negative correlation.

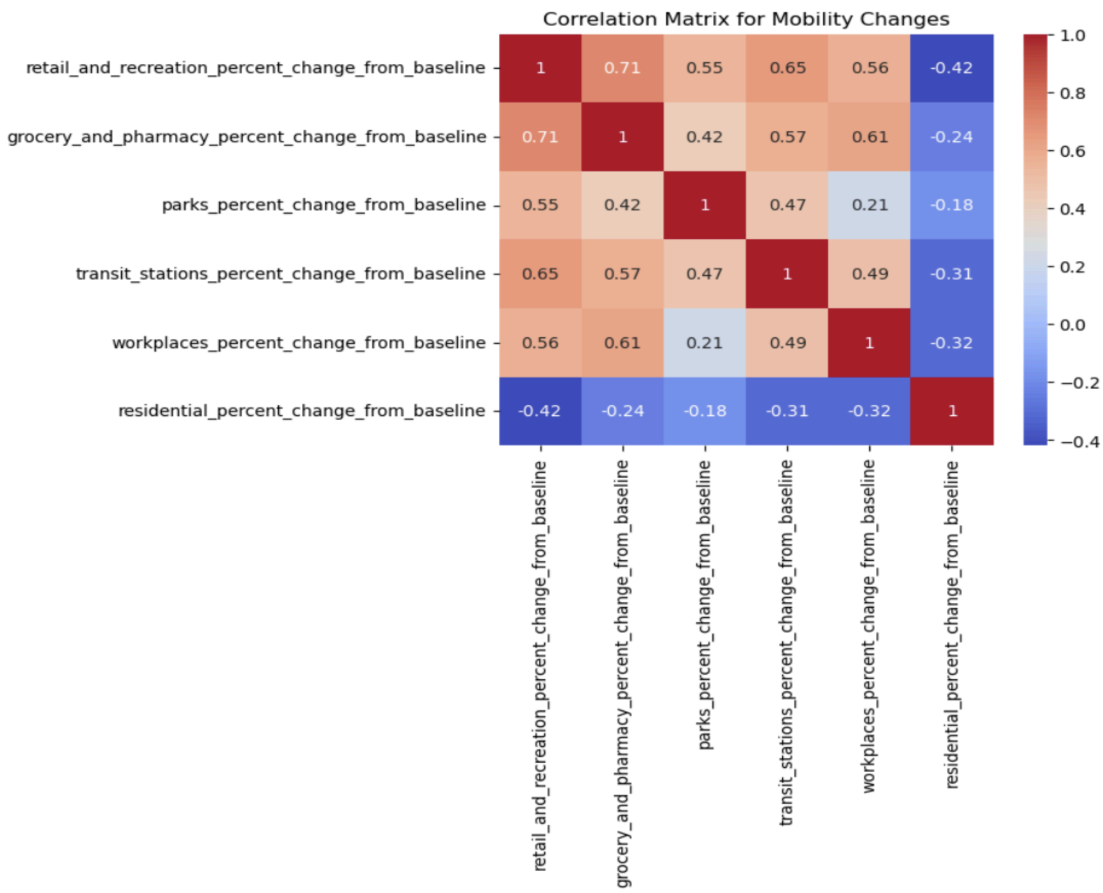


Figure (7): Correlation heatmap for mobility variables.

It is evident from the initial observation that all mobility variables are positively correlated with each other except residential, which is negatively correlated; this may also determine why residential was more right-skewed in the distribution plot. A strong positive correlation is observed between retail and recreation change and grocery and pharmacy as these two variables are interlinked.

A further attempt to visualise the distribution of mobility data was conducted using box plots. However, due to the high variance in the mobility data, the box plots were difficult to interpret. The same issue persisted with violin plots. To address this, the Z-score method was applied. Z-score measures the number of standard deviations a data point is away from the mean in a way to identify outliers ("Z-Score," n.d.). It is calculated as follows;

$$z = \frac{(X - \mu)}{\sigma}$$ ("Z-Score," n.d.)

In this analysis, X represents the percentage change in mobility for a given country in a specific year,while μ denotes the mean mobility change percentage for that variable across all countries. The symbol σ indicates the standard deviation of the mobility change for that variable. Z-scores were calculated for each mobility variable, specifically filtered for the years 2020, 2021, and 2022.

The threshold for identifying extreme values was set at 9. This choice was made due to the large size of the dataset, allowing for the identification of particularly significant deviations in mobility trends. Data points with Z-scores greater than 9 (upper bound) or less than -9 (lower bound) were categorised as extreme values. This threshold was selected after several trials and analyses, as it effectively highlighted unusual trends while minimising the risk of overlooking noteworthy changes.

It is important to note that these extreme values were not treated as outliers in this analysis. Instead, they were retained, as they offered valuable insights into countries experiencing the most dramatic shifts in mobility. This focus on extreme values aligns with the objectives of this study, which aims to uncover significant trends in mobility changes during the COVID-19 pandemic.

3.4 Time Series and Geospatial Analysis of Mobility Patterns - Google Mobility reports

This section details the application of time-series and geospatial methods to track and analyse mobility trends during the COVID-19 Pandemic. The methods were inspired by similar approaches in prominent studies such as *Our World in Data* (Mathieu et al., 2020a) and extended with statistical and clustering techniques to gain deeper insights into mobility changes.

Global time series analysis of Mobility trends

The first step was a similar approach to the methods employed by *Our World in Data* (Mathieu et al., 2020a) in their COVID-19 Mobility analysis. In this study, 7-day averages were also used to plot a graph for each mobility variable individually. It was considered ideal for smoothing out daily fluctuations while still preserving short-term trends. Using weekly averages helps eliminate noise caused by day-to-day variations, providing a clearer picture of general trends. A similar approach, which also utilised 7-day averages, was also applied in the research conducted by Kishore (Kishore et al., 2021), which found that weekly averages offered the best compromise between short-term trend visibility and noise reduction in mobility data during COVID-19.

To provide further clarity and context, key global events that occurred during the pandemic were highlighted. These included:

- **World Health Organisation's (WHO) declaration of COVID-19 as a pandemic** on 11th March 2020 (Cucinotta and Vanelli, 2020)
- **The First lockdown (March-May 2020)** marked the initial global response to the pandemic. Dates obtained based on Wikipedia's report ("COVID-19 lockdowns by country," 2024). By the end of March 2020, over 100 countries had imposed either a full or partial lockdown ("Coronavirus," 2020)
- **The Second wave and Lockdown (December 2020 - February 2021)** renewed restrictions as cases surged. Dates based on the report from Wikipedia ("COVID-19 lockdowns," 2024), the majority of countries imposed a second lockdown between December 2020 and February 2021
- **The peak of the Delta variant (June - August 2021)**: Development of a contagious variant, with the peak noted in August 2021 (De La-Cruz Hernández and Barrera-Badillo, n.d.).
- **Omicron surge (December 2021- February 2022)**, the emergence of a new variant in late November ("One year since the emergence of COVID-19 virus variant Omicron," n.d.)

Heatmap visualisation of mobility changes

The variance inflation factor (VIF) was calculated to detect multicollinearity. The formula used to calculate VIF is;

$$VIF_i = \frac{1}{1 - R_1^{\ 2}}$$

("Variance Inflation Factor (VIF)," n.d.)

Where $R_i^{\ 2}$ is the coefficient of determination obtained by regressing the i^{th} variable against all other variables ("Variance Inflation Factor (VIF)," n.d.)

Calculating the Variance influence factor was the most suitable measure because it calculates the extent of multicollinearity by assessing how much the other variables in the dataset explain a variable. By identifying variables with high VIF values, it enabled to determine which variables were highly correlated and potentially redundant. Multicolinearity is present when the calculated VIF is between 5 and 10 (Kim, 2019).

	Feature	VIF
0	retail_and_recreation_percent_change_from_base...	2.196852
1	workplaces_percent_change_from_baseline	1.414008
2	residential_percent_change_from_baseline	1.539676
3	parks_percent_change_from_baseline	1.259022
4	grocery_and_pharmacy_percent_change_from_baseline	1.671512
5	transit_stations_percent_change_from_baseline	1.576982

Figure(8): Table Showing Variance Inflation Factor (VIF) scores for mobility variables.

The VIF scores presented provide insight into the multicollinearity among the mobility variables analysed. All features exhibit VIF values below 5, indicating that multicollinearity is not a significant concern for these variables. The Retail & Recreation variable shows the highest VIF at 2.20, suggesting a moderate correlation with other mobility categories but still within acceptable limits. Other variables, such as Workplaces (1.41) and Residential (1.54), reflect low multicollinearity, affirming their suitability for clustering and predictive modelling.

Data preparation and adjustment with shapefile

The next stage of mobility analysis involved geospatial visualisation, which was conducted using the GeoPandas library, which was designed for spatial data analysis. To plot a world map, a shapefile built in the GeoPandas library *'naturalearth_lowres'* was loaded to provide geographical boundaries necessary for plotting mobility changes on a map. The shapefile contains data such as '*country*', '*population estimate*', '*continent*' and '*geometry*'. The shapefile gives the boundaries for all countries in the world, making it simple to create choropleth maps.

The mobility data was merged with the data from the shapefile by country name. - '*country_region*' from the Google mobility dataset was mapped to '*country*' in the shapefile. However, an issue was encountered. Initially, when trying to plot the data, many countries were not being mapped despite multiple attempts. To resolve this, all unique country names from both datasets (the shapefile and the Google Mobility dataset) were extracted and converted into sets for comparison. A direct comparison was conducted to identify discrepancies between the two datasets. The process revealed that 16 country names in the Google Mobility dataset did not have a direct match in the shapefile (these were *'Mauritius', 'Cape Verde', 'Aruba', 'The Bahamas', 'Bahrain', 'Hong Kong', 'Malta', 'Liechtenstein', 'Barbados', 'Myanmar (Burma)', 'Dominican Republic', 'Bosnia and Herzegovina', 'Antigua and Barbuda', 'Réunion', 'Singapore' and 'United States'*), while 58 countries in the shapefile were not present in the Google dataset. Some examples of the discrepancies in country names included: '*United States*' in the Google dataset was denoted as '*United States of America*' in the shapefile. Territories like '*Hong Kong*', '*Aruba*', and '*Réunion*' had no match in the shapefile, potentially due to being recognised as separate regions or territories rather than independent countries in the shapefile data. The unmatched countries were manually mapped to their correct counterparts in the shapefile for seamless integration. Countries without a direct match were excluded.

To better understand how mobility evolved, the absolute difference between specific time frames was calculated as follows;

$$Absolute\ Differerence_{\ Y1-Y2} = |\,Average\ mobility\ in\ Y2 - Average\ Mobility\ in\ Y1|$$

(GeorgiGeorgiev-Geo, n.d.)

Where Y relates to a specific date/year, the purpose of using absolute difference was to measure the magnitude of change without bias. This was computed for 2020 - 2021 and 2021 - 2022. The findings were then sorted to find countries with the largest increases and smallest changes for each year and each variable.

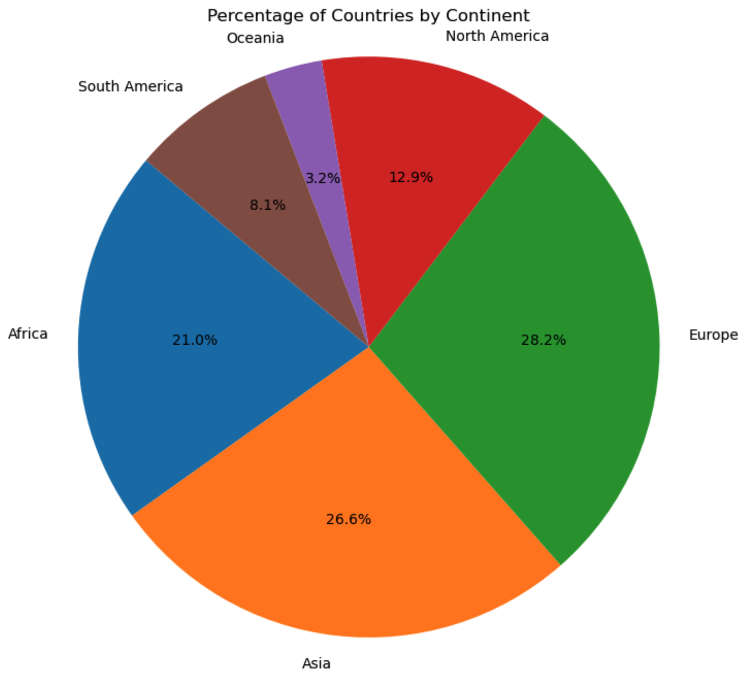
Interactive maps have proven highly effective for storytelling, as demonstrated by Our World in Data in their analysis of COVID-19 (Mathieu et al., 2020b). There was also a focus on specific key events during the pandemic; snapshots were drawn for key events and periods that applied globally, as mentioned earlier. These included the WHO declaration of the Pandemic on the 11th of March 2020, the First global lockdown (While exact timings varied of lockdowns by country, April 2020 was generally the period when most countries had stringent measures in place), Delta variant peak (August 2021 was chosen as the period for analysis for the delta variant as it is when the peak of global cases related to the Delta variant (De La-Cruz Hernández and Barrera-Badillo, n.d.)) and Omicron surge (January 2022 was selected as the peak month for this variant ("One year since the emergence of COVID-19 virus variant Omicron," n.d.)). This would help identify how key events or surges influenced global mobility patterns and allow for comparisons with other periods. Countries with the most significant changes between the years were identified for each time period. The findings were compared to existing visualisations and analyses, such as those provided by Our World in Data (Mathieu et al., 2020b), to validate trends and ensure an accurate interpretation of how mobility evolved.

Visualising Global Mobility Patterns by Continent

It was identified that looking at mobility trends at the continent level would be a good way to gain a deeper understanding, moving from a global perspective to a more detailed continental focus. While this approach may not capture the intricate variations within individual countries or specific locales, it still offers critical insights into broader regional trends influenced by socioeconomic factors, government policies, and cultural contexts.

The study of (Mistur et al., 2022) emphasises the significant influence of peer relationships on countries' policy decisions, particularly in the context of social distancing measures during the COVID-19 pandemic. It states, "*Countries are more likely to implement a policy change the very next day after a peer country changes its social distancing policies."* This highlights the immediate effect of neighbouring countries' actions on a country's own policies. Additionally, the research identifies strong support for *"geographic, political, and language peer relationships"* as significant predictors of policy adoption, indicating that countries tend to mirror the social distancing policies of their peers. Specifically, the study notes, *"A country's social distancing stringency index is 0.76 higher for each level increase in the social distancing stringency index of their neighbours."* This shows that shared geographical and cultural factors can lead to aligned policy responses, even when countries face different internal conditions. Interestingly, the findings also suggest that the actual number of COVID-19 cases in a country does not significantly drive policy choices, which implies that the context of a pandemic does not overshadow the influence of peer behaviour in policy adoption. The study concludes that "*countries appear to mimic peer countries' policy choices, regardless of whether or not those peers have a high prevalence of COVID-19*," emphasising the role of imitation and emulation in the policy environment.

The initial step was to integrate the countries within the mobility data with the appropriate continents using the shapefile *(naturalearth_lowres)* used previously to map countries. A new column, *'continent'*, was created. To better understand the distribution of countries across continents within the dataset, a count of unique countries per continent was obtained. To visualise this distribution, a pie chart was generated, illustrating the dominance of each continent in terms of the number of countries represented, as shown in *Figure (9)*. The results showed that Europe and Asia were the most represented, accounting for 28.2% and 26.6% of the total countries, respectively, while Oceania had the smallest share at 3.2%. It is important to emphasise that the representation is specific to the countries in the dataset and not a reflection of global distribution. The continent-level analysis only includes 124 countries, as shown in *Figure (10)*, and not all 195 countries are recognised globally ("How many countries are there in the world?" n.d.). The purpose of this pie chart is to identify potential over representations, which may impact the interpretation of mobility trends on a continent level. However, it is also important to consider that continents such as Europe and Asia inherently contain more countries than Oceania. This leads to a larger variety of mobility behaviours in Europe and Asia. In the instance of this study, this does not create an imbalance but instead allows for a more comprehensive understanding of regional mobility patterns. The greater number of representations from the likes of Europe and Asia provides a broader scope, as the analysis focuses on relative change rather than absolute counts.



Figure(9) Pie Chart distribution of countries to continents.

```
Number of countries assigned to each continent:
continent
Africa           26
Asia             33
Europe           35
North America    16
Oceania           4
South America    10
Name: country_region, dtype: int64

Total number of countries: 124
```

Figure(10) Table showing the number of countries in each continent

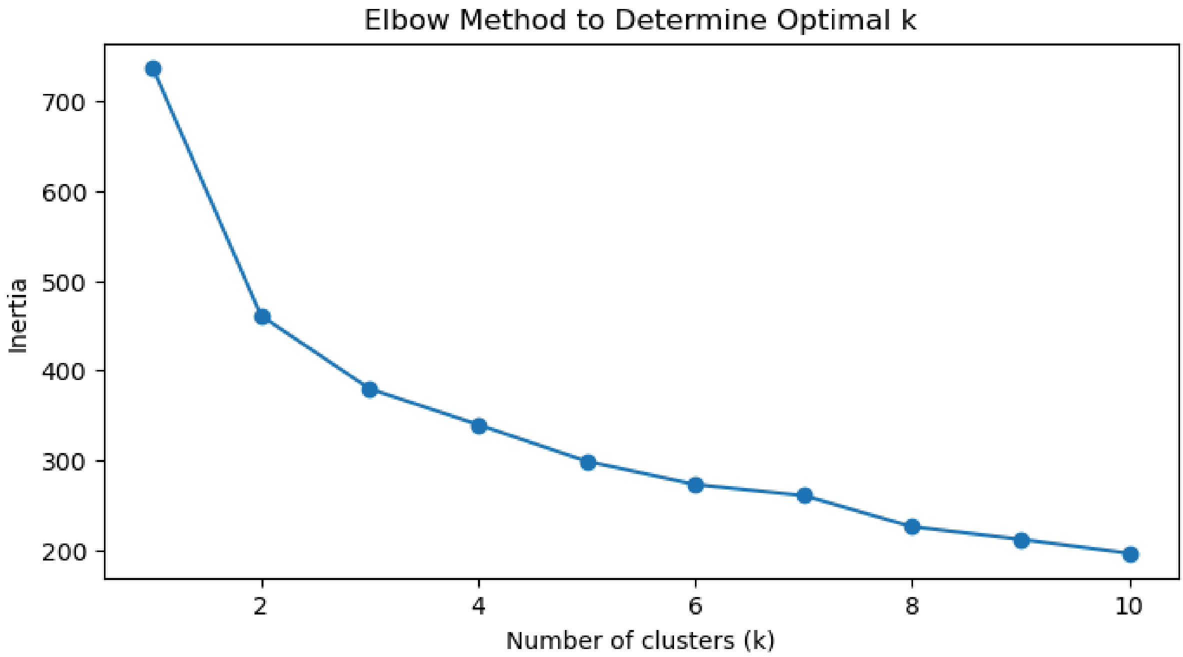
3.5 K-Means Clustering of Mobility Patterns

Clustering techniques were applied to identify similarities and group countries based on their mobility changes during the pandemic. The K-means clustering method is an unsupervised machine-learning algorithm for partitioning data into clusters based on feature similarity (Sharma, 2019). K-means was particularly suitable for this study as it is computationally efficient for large datasets and provides clear and interpretable clusters. This decision was further supported by other research, such as that of Nielsen et al. (2021), which used K-means to analyse cities in the USA with similar mobility and case counts during COVID-19. A similar approach in this study enabled the identification of groupings of countries that exhibit similar mobility trends.

Rather than using the complete time series data, which may include daily or weekly observations leading to high dimensionality, this analysis utilised aggregates from key periods defined by significant pandemic-related events: the WHO declaration of COVID-19 as a pandemic, the first lockdown, the second wave and lockdown, the peak of the Delta variant, and the Omicron surge. This approach reduces dimensionality while capturing the essential changes in mobility patterns during critical phases of the pandemic.

Before clustering, mobility variables were aggregated over the five defined time periods, and mean values for each mobility variable were calculated for the described time frames. Although all variables were percentages, they varied in their ranges; therefore, standardisation was necessary. Standardisation was performed using the StandardScaler function from the Scikit-learn library, ensuring that each variable had a mean of 0 and a standard deviation of 1. This process allowed each variable to contribute equally to the clustering process, preventing variables with larger ranges from dominating.

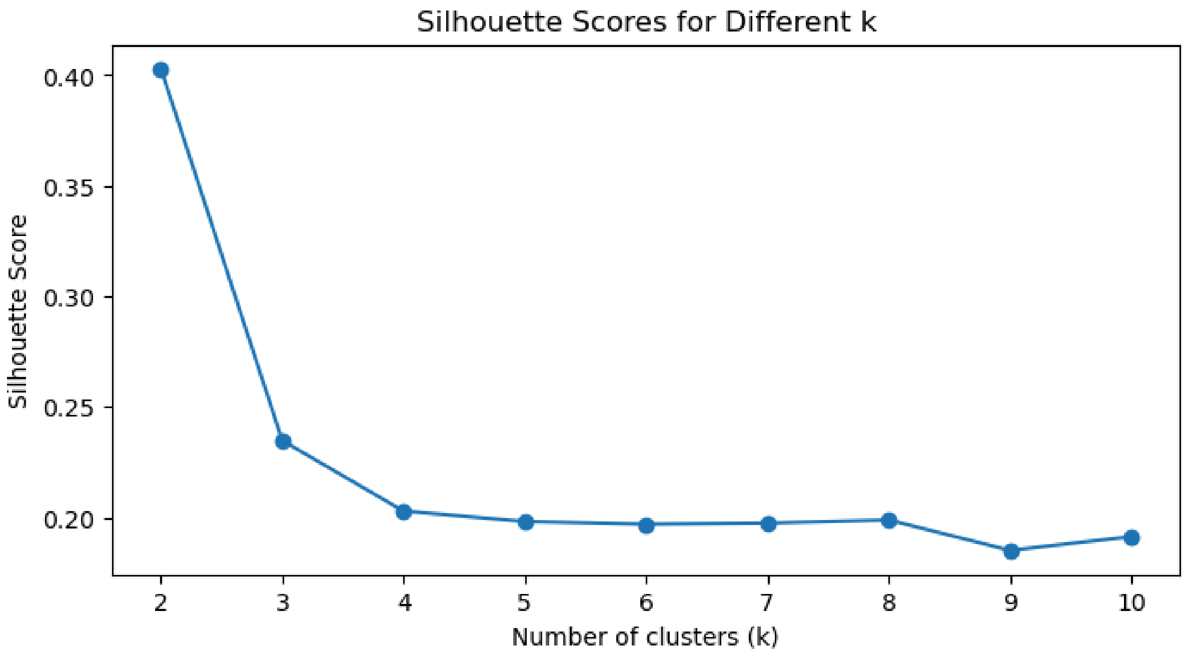
The optimal number of clusters (K) was determined using two methods: the elbow method and the silhouette score. The elbow method examines the relationship between different numbers of clusters and the within-cluster sum of squares (Basil, 2021). As the number of clusters increases, the within-cluster sum of squares also rises because more clusters result in smaller distances between data points and centroids. The *'elbow'* point marks where the addition of more clusters leads to diminishing returns in reducing the within-cluster sum of squares. A study examining similar contexts applied this method to find the optimal number of clusters in mobility analysis, using visual identification of the elbow point for decision-making ("Elbow method plot for obtaining the optimum number of clusters," n.d.).



Figure(11): Line graph showing results from elbow method - (All mobility variables combined)

Based on the graph, the point of diminishing returns with the addition of more clusters, also referred to as the 'elbow' point, highlights 3 clusters as the ideal number of clusters.

Silhouette scores measure how similar data points are to their own cluster compared to other clusters. A score between -1 and 1 indicates clustering quality, with scores closer to 1 suggesting strong clustering. A score of 0 indicates points are equally close to other clusters, while a score near -1 indicates poor clustering results (Gültekin, 2023). Using a combination of the elbow method and silhouette score ensured that the selection of the number of clusters was both visually interpretable and statistically validated. Based on the silhouette score obtained, the highest silhouette score was seen with 2 clusters.



figure(12): Line graph showing silhouette score graph

Based on the two scores, the ideal number of clusters was determined to be 2. As indicated by the results of the two measures, K= 2 clusters gained the highest silhouette score- meaning clusters are well-defined and distinct. Furthermore, the drop in inertia for the elbow method between clusters 2 and 3 is not significant. Hence, the final value for *K* adopted was 2.

Once the optimal number of clusters was identified, K-means clustering was applied, resulting in each country being assigned to a specific cluster.

Clustering for each mobility variable individually

Additionally, clustering was performed individually for each of the six mobility variables across the specified time periods. This approach allowed for the observation of patterns within specific mobility contexts. By analysing each mobility variable individually, clustering helps uncover specific contexts and variations that may not be apparent when examining mobility data as a whole. This approach facilitates targeted insights into the mobility responses of different regions, highlighting similarities and differences among countries based on their mobility patterns. As done previously, the optimal number of clusters was determined individually for each variable using the elbow method and silhouette score. The table below shows the results for each mobility variable's elbow and silhouette scores and the final chosen number of clusters.

Mobility Variable	Optimal Elbow Score	Optimal Silhoutte Score	Silhouette Score	Final Number of Clusters
workplaces_percent_change_from_baseline	**3**	**2**	**0.58**	**3**
retail_and_recreation_percent_change_from_baseline	**3**	**3**	**0.59**	**3**
grocery_and_pharmacy_percent_change_from_baseline	**3**	**2**	**0.649**	**3**
parks_percent_change_from_baseline	**3**	**2**	**0.74**	**3**
transit_stations_percent_change_from_baseline	**3**	**3**	**0.60**	**3**
residential_percent_change_from_baseline	**3**	**2**	**0.59**	**3**

Figure(13): Table showing elbow score & silhouette score, and ideal clusters for each mobility variable

To ensure simplicity and maintain consistency across the analysis, a uniform cluster size of K=3 was chosen for all variables.

3.6 Analysis of Mobility patterns for G20 and LDC countries

A focused analysis was conducted on the Group of Twenty (G20) and the Least developed countries (LDCs) to investigate how mobility patterns evolved between 2 contrasting economies throughout the pandemic. The G20 compromises of 19 countries (*Argentina, Australia, Brazil, Canada, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Turkey, United Kingdom, United States of America*) and the European Union. G20 countries apportion 85% of the global GDP ("What Does the G20 Do?" n.d.). On the other hand, LDC countries are characterised by their weak economies and human resources, making them particularly susceptible to global pandemics. A list of LDCs was obtained from the United Nations website ("List of LDCs | Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries and Small Island Developing States," n.d.)

The decision to include LDCs in this analysis comes from the need to understand how vulnerable economies respond to mobility restrictions compared to more developed nations. The LDCs present in the dataset were *Afghanistan, Angola, Bangladesh, Burkina Faso, Haiti, Zambia, Mali, Mozambique, Niger, Rwanda, Senegal, Tanzania, Uganda and Yemen*. Monthly averages for each mobility variable were calculated for both G20 and LDC countries, and the data was aggregated based on either G20 or LDC to enable comparative analysis.

3.7 Data integration for further analysis of mobility patterns

Following the initial use of the Google Mobility data, it became evident that integrating additional datasets would provide a deeper understanding of mobility patterns during the COVID-19 pandemic. The incorporation of diverse datasets enhances the research's robustness and allows for a comprehensive analysis of how various other factors influence mobility trends.

Datasets Used

Four key datasets were utilised in this process:

1. **Our World in Data COVID-19 Dataset** ("COVID-19 Data Explorer," n.d.): This dataset, comprising 429,435 rows and 67 columns, contains extensive coverage of various aspects of COVID-19 metrics. It includes total cases (*cumulative counts*), new cases (*daily reported counts*), total deaths, and critical containment variables such as hospital beds per thousand and life expectancy for every country. Additionally, it provides demographic data, including the population of each country and the Human Development Index (*HDI*). The dataset spans from January 5, 2020, to August 4, 2024. This temporal range is particularly useful as it captures the entire duration of the pandemic and allows for analyses of trends over time, making it a critical resource for assessing the interplay between COVID-19 metrics and mobility behaviours.
2. **World Health Organization (WHO) Daily Cases and Deaths** ("COVID-19 data | WHO COVID-19 dashboard," n.d.): The WHO dataset provides daily updates on new and cumulative COVID-19 cases, covering the period from April 1, 2020, to September 22, 2024. This dataset is valuable for answering the research objectives as it provides timely and precise data on the pandemic's progression. The daily updates enable a dynamic understanding of how fluctuations in case numbers may correlate with changes in mobility patterns.
3. **Stay-at-Home Restrictions Dataset** (Mathieu et al., 2020c): This dataset, derived from research conducted by Our World in Data, outlines global stay-at-home restrictions, including lockdown measures. It spans from January 1, 2020, to December 31, 2022, and categorises restrictions into four levels, ranging from no measures (0) to extreme measures (3). These were detailed on Our World in Data as 0 being no measures, 1 advised to stay at home, 2 lockdowns with exceptions such as exercise, shopping, etc. and 3 lockdowns with minimal exceptions.

This dataset is useful for the study as it provides context on how governmental restrictions affect mobility behaviours. By incorporating this dataset, it can build upon existing research, enhancing understanding of the relationship between policy measures and mobility patterns during the pandemic.

4. **Government Stringency data** (Mathieu et al., 2020c): The inclusion of government stringency data obtained from *Our World in Data* was found to enhance the subsequent analysis. This dataset measures nine response indicators, including workplace closures, travel bans, school closures, cancellations of public gatherings, stay-at-home requirements, information campaigns, restrictions on internal movements, and international travel controls. The mean score is calculated based on combining all nine variables, providing a scale from 0 to 100, where 100 indicates the strictest measures. This can be used in correspondence with mobility analysis during the key periods defined to assess how stringency and mobility overlapped.

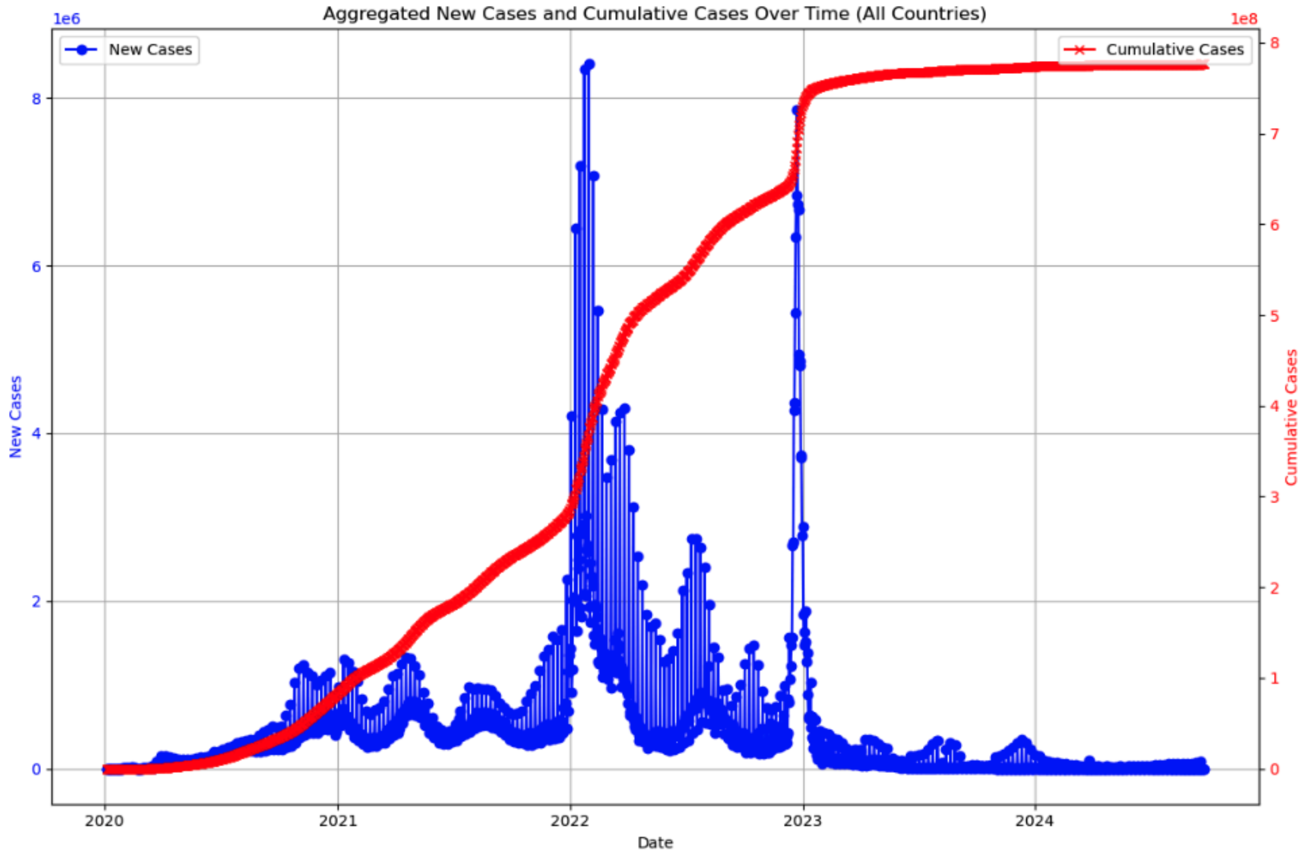
These datasets collectively provide a robust framework for understanding mobility changes in relation to COVID-19 trends and governmental responses. They match the required time periods for the analysis, ensuring comprehensive coverage of the pandemic's various phases.

Data Preparation and Mappings

The initial step involved importing the datasets into the analysis environment using the Pandas library in Python. Each dataset was explored individually to understand its structure and key variables. Specific variables were chosen based on their relevance to the research objectives, particularly those that would enable the examination of mobility patterns alongside COVID-19 metrics.

A correct mapping of country names was established to address variations in naming conventions across datasets. For instance, discrepancies such as "*Cote d'Ivoire*" and "*Côte d'Ivoire*" were standardised to ensure consistency. This mapping process was essential for reducing discrepancies during the merging of datasets with the original Google Mobility Reports. The datasets used were selected based on their completeness and relevance, ensuring that the majority of entries were available for analysis. Second, the key variables of interest had sufficient data coverage across the defined time periods, which minimised the potential impact of any missing values on the overall analysis.

The WHO dataset was mapped according to the date and country name columns, and the modified dataset now included '*New_cases*' and '*Cumulative_cases*,' which were chosen for their relevance to the analysis of how COVID-19 trends affected mobility behaviours. The dataset was extended up to August 4, 2024, to support predictive modelling later on, even though there was no corresponding mobility data for that period. *Figure (14)* below shows aggregated cumulative cases for all countries and aggregated daily new cases for all countries.



Figure(14): Line graph of global cumulative cases and new cases from 2020 to 2024

The integration of these datasets provides a comprehensive and nuanced view of mobility patterns during the COVID-19 pandemic, creating a solid foundation for understanding how public health measures and COVID-19 trends influenced mobility behaviours over time.

3.8 Hierarchical Clustering

Data Preparation

Hierarchical clustering was conducted. This method is expected to be particularly useful for understanding the relationships among countries based on their mobility responses during the COVID-19 pandemic. By using hierarchical clustering, the data can be visualised in a dendrogram format, which provides insights into how closely different countries are related regarding their mobility patterns and the implementation of stay-at-home measures. The combination of K-means earlier and Hierarchical clustering enriches the analysis.

The analysis begins by preparing the dataset, which contains mobility and stay-at-home data. To facilitate a weekly analysis, a new column called '*week start*' was created. This column represents the start date of each week by adjusting the original '*date*' column. The use of weekly aggregation is crucial, as it smooths daily fluctuations, allowing for clearer insights into trends and changes in mobility behaviour.

The steps involved in hierarchical clustering;

1. **Data Preparation**: The input data consisted of aggregates calculated from specific key periods during the pandemic mentioned earlier (similar to k-means clustering). This was a deliberate choice to avoid the high dimensionality associated with using the complete time series, which can include daily or weekly data. By aggregating the data based on significant time periods—such as the WHO declaration and various lockdown phases— it was ensured that the analysis was focused on relevant trends and behaviours and the more significant parts of the pandemic.
2. **Aggregation for Countries**: The data was aggregated at the country level to calculate average stay-at-home requirements and average weekly new cases across the defined key time periods. This aggregation is essential for identifying countries that exhibit notable mobility and public health trends, allowing for a clearer interpretation of clustering results.
3. **Selection of Significant Countries**: The analysis specifically targeted significant countries, defined as those with the highest average new COVID-19 cases during the key time periods. This focus enables the clustering analysis to concentrate on countries where the impact of stay-at-home measures is likely to be most pronounced, enhancing the relevance of the results.

4. **Imputation of Missing Values**: Missing data points in the aggregated features were addressed using the mean imputation strategy. This step ensures that the dataset remains robust and complete, which is critical for accurate clustering outcomes.
5. **Normalisation**: The features (average stay-at-home requirements and new cases) were normalised using a standard scalar. Normalisation is a crucial preprocessing step in clustering analyses, as it ensures that all features contribute equally to the distance calculations used during the clustering process.
6. **Determine number of clusters:** The number of clusters was determined by setting a threshold distance of 10 for hierarchical clustering. This value was chosen based on a visual inspection of the dendrogram, which illustrates the hierarchical relationships among countries based on their similarities in average stay-at-home requirements and new COVID-19 cases. The threshold allows for the identification of distinct clusters while preventing overly granular subdivisions that could arise from a lower threshold. By selecting a threshold of 10, the analysis captures significant groupings of countries, facilitating a clearer interpretation of trends within each cluster.
7. **Hierarchical Clustering**: Agglomerative clustering was performed using the Ward linkage method. This method minimises the variance within each cluster and is particularly effective for identifying hierarchical structures within the data.
8. **Global Dendrogram Visualization**: A global dendrogram was plotted to visualise the hierarchical clustering of all countries, highlighting the overall clustering patterns on a global scale. This visualisation provides a comprehensive overview of how countries relate to one another based on their public health measures and mobility patterns.

3.9 Individual Country-level Analysis

A selection of 11 countries was made for further individual-level investigation: the *United Kingdom, United States of America, Sweden, Australia, South Korea, Mongolia, Libya, Argentina, Bangladesh, Italy, and Mali*. This diverse selection is beneficial for the study for several reasons. Firstly, it ensures a wide geographic representation that is crucial for understanding how governmental responses to COVID-19 varied across different regions and cultural contexts. Secondly, the group includes both developed and developing countries, such as the United Kingdom, Australia, and Sweden, alongside lower-income countries (LDCs) like Mali and Bangladesh. This contrast allows for an examination of how socioeconomic factors influence governmental responses and mobility trends, thereby enriching the analysis. Additionally, the selected countries exhibited different restrictions during the pandemic;

for example, Australia implemented stringent lockdown measures, whereas Sweden opted for a more relaxed approach. Such variations provide valuable insights into the effectiveness of different strategies and their impacts on mobility patterns. Furthermore, the selection was also determined by earlier clustering and mobility pattern analysis, for instance, looking at countries that showed significantly greater mobility than the rest, i.e. Libya and Mongolia. The decision to conduct a country-level analysis enhances the study by allowing for a more specific examination of the unique factors influencing mobility trends and responses to government policies.

The following key details were obtained from the dataset "National responses to the COVID-19 pandemic" (“National responses to the COVID-19 pandemic,” 2024), which documented national responses and containment measures for every country, along with the dates of policy events:

- **Start Date**: The date when a policy event (e.g., lockdowns) commenced.
- **End Date**: The date when the policy event ended.
- **Event Description**: A brief description of the policy event.

Mobility data for the selected countries was aggregated on a weekly basis. A function was defined to visualise the relationship between new COVID-19 cases and policy events, with policy periods shaded to denote the timing of specific interventions. Specifically, stay-at-home requirements were chosen for this analysis, as they provide a more direct correlation to changes in mobility behaviour compared to other containment measures such as social distancing and restrictions on the size of gatherings. While these measures also influence movement patterns, stay-at-home orders directly restrict individuals' ability to leave their homes for non-essential activities, making them a more immediate indicator of mobility changes. This visualisation offers a broad view of how government actions influenced mobility trends during the pandemic for the selected countries.

3.10 Linear regression for mobility trend prediction

This section outlines the methods employed for applying linear regression to predict future mobility trends based on historical data. Linear regression is expected to be particularly useful in this context as it allows for the identification of relationships between independent variables (such as new COVID-19 cases and stay-at-home requirements) and dependent variables (mobility trends across various sectors). By quantifying these relationships, linear regression provides a statistical foundation for forecasting future mobility patterns, which can be critical for policymakers, businesses, and public health officials.

Data Preparation

Initially, the dataset underwent dimensionality reduction to include only essential columns, such as '*Cumulative Cases'*, '*Stay-at-Home Requirements*', and various mobility metrics. To ensure the accuracy of the results, any rows containing NaN (no entries) values in key columns were removed, making the dataset more manageable.

Global Data Analysis

Weekly averages for each mobility variable and cumulative cases were calculated globally. This analysis involved calculating the mean for each mobility metric and cumulative cases across all countries on a weekly basis. This aggregated data served as the foundational dataset for training the regression models.

The features used in the regression analysis included average cumulative cases and average stay-at-home requirements. These were selected based on previous studies indicating their direct impact on mobility behaviour. The study by Chakraborty et al. (2023) applied a similar method specifically for the United States, reinforcing the validity of this approach for this specific analysis.

Cluster-Specific Modelling

Linear regression models were trained for each mobility target variable based on clusters obtained from hierarchical clustering. This approach allowed for the aggregation of countries into distinct groups, reflecting shared mobility trends and public health responses influenced by similar socioeconomic and cultural contexts. The hierarchical clustering method was chosen for its ability to identify natural groupings in the data, providing a nuanced understanding of how different regions respond to factors such as cumulative cases and stay-at-home orders.

Countries were aggregated based on the clusters they belonged to, ensuring that the analysis focused on meaningful similarities in mobility behaviour across regions. The training data for each cluster consisted of historical values up to a specified cutoff date (the last entry of mobility data on 13/10/2022), while the testing data included subsequent weeks until 04/08/2024 (present-day). This temporal split ensured that the models were trained on prior data before making predictions about future trends. The predictions generated by the regression models targeted the period extending from the end of the training data (13/10/2022) to the specified future date (04/08/2024).

3.11 Analysing the impact of mobility restrictions on the Global Economy and Labour market.

Global Economy

To analyse the impact of mobility restrictions on both the economy and the labour market, the first dataset used is the global GDP dataset obtained from Our World In Data ("Global GDP over the long run," n.d.). This dataset is particularly relevant as it provides a comprehensive overview of Gross domestic product (GDP) worldwide over time, dating back from 1 CE to 2022. This ensures it covers the time period required. GDP provides a detailed understanding of economic growth and is regarded as the best economic performance indicator ("Top 10 U.S. Economic Indicators," n.d.). This is crucial for understanding the broader economic context prior to and during the COVID-19 pandemic.

Analysing GDP Growth Data- Country level

The second dataset used for this objective was also sourced from Our World in Data, containing annual GDP growth, specifically the percentage change in GDP from one year to the next for 196 countries ("Annual GDP growth," n.d.). This dataset is divided into two key columns: one column contains percentage change observations spanning from 1980 to 2023, providing the latest and most accurate figures for the annual percentage change in GDP for all 196 countries. The second column includes forecasted values extending to 2029.

The inclusion of this dataset is essential for the study as it allows for a detailed examination of economic growth trends in relation to mobility restrictions during and after the COVID-19 pandemic at the country level. By analysing both historical observations and future forecasts, the study can assess how immediate economic impacts have evolved over time and predict potential trajectories influenced by ongoing mobility dynamics. This dataset builds upon the previous global GDP dataset by providing a more granular view of annual growth rates. Countries with the highest GDP alongside the selected countries for this study (*United Kingdom, United States of America, Sweden, Australia, South Korea, Mongolia, Libya, Argentina, Bangladesh, Italy, and Mali)* were looked at alongside a side-by-side comparison of the available G20 and LDCs.

Analysing labour market dynamics: Unemployment data

"The unemployment rate is the proportion of labour force that is not in the workforce" ("9. The labour market," n.d.). Unemployment serves as a critical feature for analysing labour market

dynamics because it directly reflects the economic health of a nation and indicates how effectively an economy is utilising its workforce. High unemployment rates can signal economic distress, while low rates may suggest robust economic activity and effective job creation. Understanding unemployment levels provides insight into the capacity of the labour market to absorb shocks, such as those induced by mobility restrictions.

The dataset used for this analysis was also obtained from Our World in Data ("Unemployment Rate," n.d.), containing unemployment data for 114 countries from 1980 to 2029. Similar to the annual GDP growth dataset, this data is split into two key columns: one for actual figures spanning 1980 to 2023 and another for forecasted figures from 2024 to 2029. This dataset is crucial as it offers valuable insights into labour market conditions over time, enabling a comprehensive examination of how mobility restrictions during the COVID-19 pandemic have influenced unemployment rates on a global scale.

Unemployment levels are particularly important in the context of mobility patterns. When mobility is restricted, such as during lockdowns, businesses often face operational challenges that can lead to layoffs and reduced hiring. Therefore, analysing unemployment rates alongside mobility data provides a clearer picture of the direct effects of public health measures on labour market outcomes.

Moreover, the correlation between GDP, unemployment rates and mobility variables was also looked at. A study by Andrei et al. (n.d.) concluded that a one-percentage-point increase in unemployment is associated with a proportional decline of 0.5% in GDP growth. This highlights the significant economic implications of rising unemployment and its detrimental effects on overall economic performance.

Labour Force Participation Data

To analyse labour force participation, this study utilises data obtained from the World Bank, which provides insights into the female labour force participation rate for individuals aged 15 and above across various countries ("World Bank Open Data," n.d.). This dataset is particularly valuable as it offers comprehensive coverage of female participation in the labour market, allowing for a deep understanding of trends and disparities over time. Analysing labour force participation is essential because it directly reflects economic power and social equity; generally speaking, higher participation rates indicate greater inclusion of women in the workforce, which can lead to improved economic outcomes for families and communities. ("Facts and Figures," n.d.)

Moreover, the dataset not only includes data for individual countries but also categorises countries into regions based on geographical and economic factors. This grouping is beneficial as it enables comparative analyses across different economic contexts and cultural settings, revealing insights into how regional policies and economic conditions influence female labour force participation. The dataset spans from 1990 to 2023, providing a long-term perspective that is critical for understanding historical trends and the impact of global events on labour markets.

This extended timeframe is significant as it encompasses several important global events that may have influenced mobility patterns and labour market dynamics, such as the Ebola outbreak (2014-2016) ("Ebola virus disease," n.d.) and the Zika virus outbreak (2014-2017) ("Zika epidemics 2014-2017," 2018). Both health crises had profound effects on public health and economic stability, particularly affecting women's participation in the workforce due to increased caregiving responsibilities and disruptions in economic activities. By including such a long timestamp, the analysis allows for a comprehensive view of how female participation rates have evolved over time, illustrating both progress and setbacks in the context of broader social and economic changes.

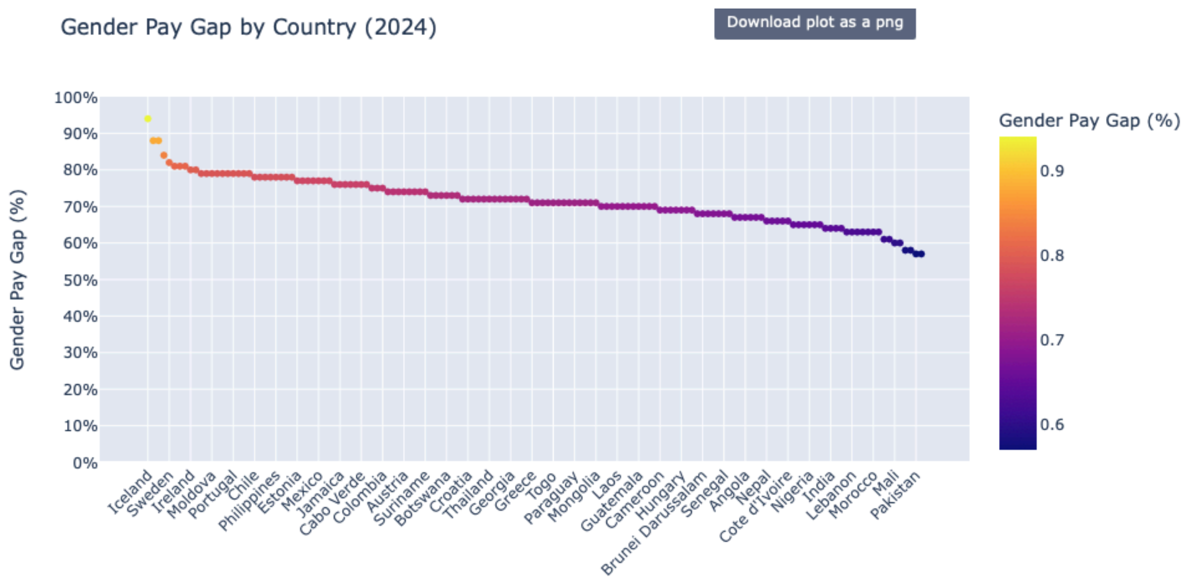
Further analysis was conducted to assess labour force participation for selected groups, including the Euro Area, European Union, Least Developed Countries (LDCs), Low Income, Middle Income, and High Income. This selection was made because these regions are already well-represented in the dataset, enabling effective comparisons and insights into how different economic contexts influence female labour force participation.

3.12 Gender Pay Gap

Global gender Pay gap

To analyse the dynamics of the global gender pay gap, this study utilises data from Statista, which provides insights into both the controlled and uncontrolled gender pay gaps from 2015 to 2024 ("Gender Pay Gap Worldwide 2024," n.d.). The dataset includes two critical measures: the Controlled Gender Pay Gap, which reflects the difference in pay between men and women after accounting for factors such as job type and experience, and the Uncontrolled Gender Pay Gap, representing the overall difference in average earnings between men and women without any adjustments. The gender pay gap is typically expressed as a ratio; for instance, a ratio of 0.75 signifies that for every dollar earned by a man, a woman earns 75 cents.

Further data was sourced from Statista, offering insights into the gender pay gap at the individual country level for 2024 ("Gender Gap Index 2024," n.d.) A scatter plot was created to visualise the current uncontrolled gender pay gap by country;



Figure(15): Scatter plot of uncontrolled gender pay gap by country in 2024

From the scatter plot, it is evident that as of 2024, Iceland has the lowest uncontrolled gender pay disparity (0.94), while Pakistan has the highest pay disparity (0.57). Furthermore, data obtained from Statista ("Workplace gender gap worldwide by type 2024," n.d.) was used. The data provides insights into various types of workplace gender gaps projected for 2024. The dataset categorises the gender gap by specific types, which include '*Females in Senior roles*', '*Women in Parliament*', ' *Share of Global workforce', 'Women's hiring into leadership positions', 'Women in STEM ', and ' Woman in non-STEM positions* '. Highlighting how disparities vary depending on the field.

Predictive Modelling

In this analysis, the Prophet model was utilised to predict the global gender pay gap, focusing on both controlled and uncontrolled scenarios while incorporating mobility, GDP, and unemployment. Prophet is specifically designed for time series forecasting, which makes it particularly suitable for this analysis. Its strengths lie in its ability to handle seasonality and trends, which are critical in economic data, allowing for more accurate predictions in contexts where the gender pay gap can be influenced by various external factors such as mobility. (Brownlee, 2020).

The analysis involved two primary sets of predictors: the first set combined mobility variables with GDP, and the second set combined mobility variables with unemployment. This approach was adopted to assess how different economic indicators alongside mobility correlate with changes in the gender pay gap. Mobility variables, reflecting shifts in economic activity, are critical as they provide insight into how changes in movement patterns can impact employment and economic participation, which are directly tied to gender disparities in pay. By incorporating GDP, the analysis could consider the broader economic scope, while the addition of unemployment data offered a wider view of labour market dynamics affecting gender pay gaps.

To generate predictions, the Prophet model was configured to forecast for the next decade, specifically until 2032. The predictions were based on the last known values of both controlled and uncontrolled pay gaps, serving as starting points for future scenarios. Three distinct scenarios were created for each type of analysis: an increase scenario, where the predictors were projected to grow at rates of approximately 0.5% to 2% per week; a steady scenario, where both variables were expected to remain constant; and a decline scenario, where both were anticipated to decrease at rates of 0.2% to 1% per week. These specific rates were selected based on historical trends to provide a realistic outlook for future developments. Furthermore, growth rates were also determined by earlier linear regression that predicted global mobility.

Initially, linear regression was considered for this analysis; however, it proved less effective in capturing the complexities of the relationships among the variables. The mean squared error for the controlled gender pay gap was recorded at 1.32×10^{-6}, which is considerably low, and with an R^2

score of 0.93, indicating a strong correlation. The uncontrolled gender pay gap exhibited a mean squared error close to zero and an R^2 score of 0, suggesting that linear regression was a good fit. However, despite these favourable metrics, the linear regression model lacked the ability to account for the dynamic and nonlinear nature of the data over time, particularly in relation to the external factors influencing mobility patterns and gender pay disparities. The Prophet model is great at managing the intricate seasonality and trend changes that often characterise economic data. Its flexibility allows for incorporating multiple seasonalities and adaptability to shifts in trend direction, making it a superior choice for this type of analysis. Prior studies, such as those conducted by (Sah et al., 2022), have demonstrated Prophet's efficacy in forecasting complex trends, notably in predicting active COVID-19 cases and new cases during different periods. This study shows the advantages of employing Prophet in capturing the interplay between mobility, GDP, unemployment, and the gender pay gap, thus providing a wider understanding of these dynamics and being able to formulate actionable insights for policymakers.

4. Results

4.1 Introduction

This chapter presents the results obtained from the analysis of mobility patterns and their impact on gender pay disparities during, prior to, and post-COVID-19. The primary focus is to examine how changes in mobility—due to various lockdown measures and restrictions—correlated with shifts in employment and the gender pay gap.

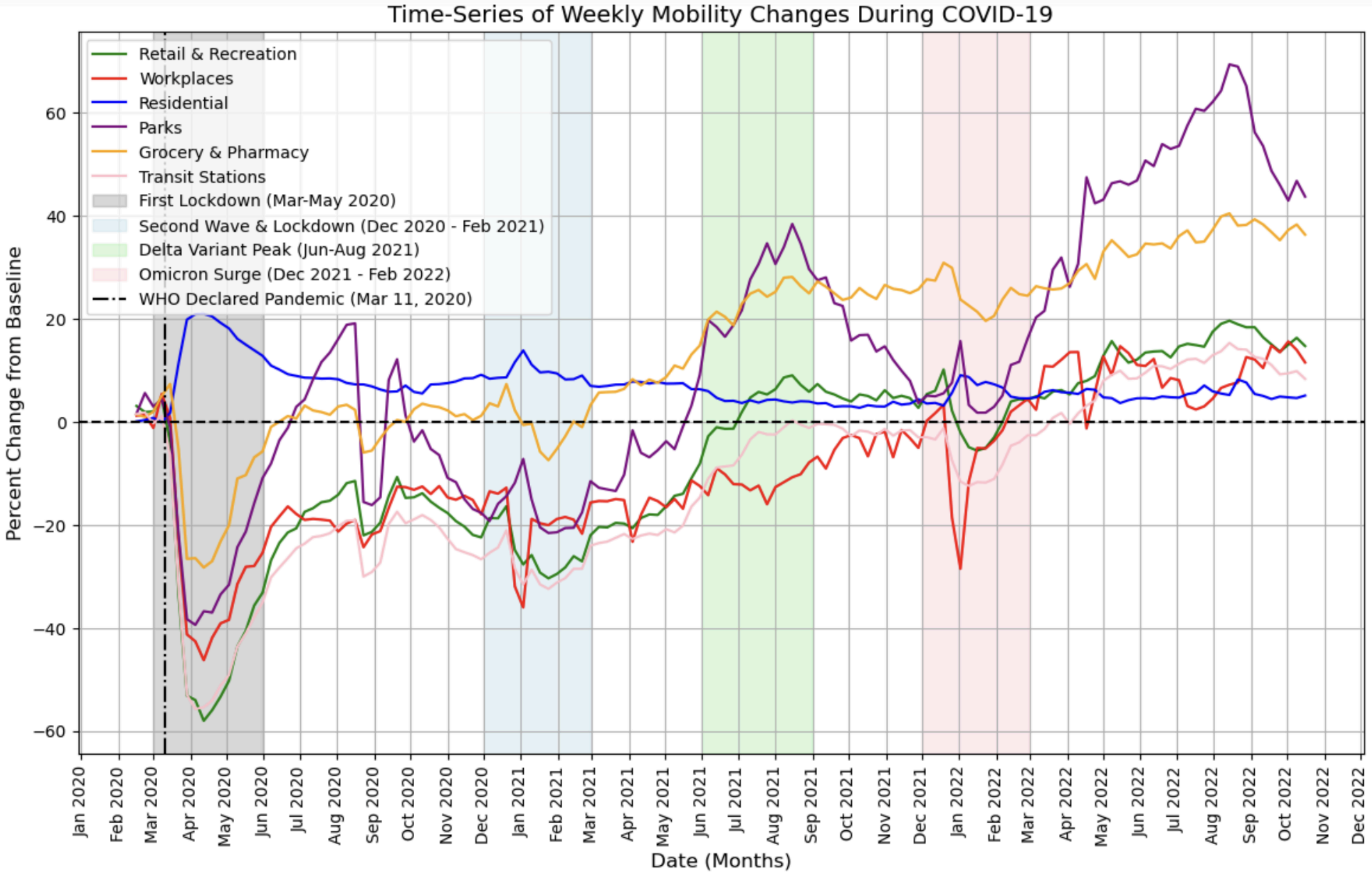
The methods employed involved merging mobility data from sources like Google Mobility Reports with country-level gender pay gap data obtained from Statista. This approach allowed for a comprehensive analysis of how mobility patterns influenced gender pay equity and labour market dynamics. The results presented in this chapter are significant in addressing the research objectives outlined previously, providing insights into the interplay between mobility, labour market changes, and gender pay disparities.

In the following sections, the results will be categorised into two main components: data analysis, clustering and predictive modelling outcomes.

4.2 Mobility Pattern Analysis

Time-Series Analysis of global weekly mobility changes across sectors during COVID-19

The line graph below illustrates the fluctuations in mobility patterns across various categories from January 2020 to November 2022. This graph provides a comprehensive view of how different mobility sectors reacted to the COVID-19 pandemic and subsequent variants. The mean was taken for each mobility variable to obtain global values.



*Figure(16)***:** *Line graph showing the percentage change from baseline mobility across various categories during the COVID-19 pandemic.*

By mid-March 2020, mobility across all categories experienced a drastic decline, coinciding with the World Health Organization's declaration of the COVID-19 pandemic on March 11, 2020. This declaration marked a significant shift in public behaviour, as strict lockdown measures were enforced worldwide based on each respective country, resulting in notable drops in mobility across sectors. For instance, the Retail & Recreation sector plummeted to nearly -60% by April 2020, reflecting a substantial decrease in foot traffic and consumer activity. Conversely, Residential mobility surged to almost +20% during this period, likely due to increased time spent at home as individuals sought to avoid virus exposure and adhere to lockdown protocols. The widespread implementation of lockdown measures from March to May 2020 explains why mobility levels across most sectors were at their lowest, with the exception of Residential.

As restrictions eased, a gradual recovery began in late June 2020, with all variables trending toward baseline levels. By early August, both Parks and Grocery mobility rebounded from negative to positive territory, with Parks climbing to approximately +20% and Grocery & Pharmacy reaching about +5%. This resurgence may have been influenced by the lifting of restrictions and a renewed interest in outdoor activities as summer approached due to an increased public interest in outdoor recreation as people sought safe, socially distanced activities. The summer season may also play a part in this. This is also backed by several studies, such as GOV UK reports that almost 50% of adults claim they spent more time outdoors than before the pandemic ("People and Nature Survey," 2022)

However, this recovery was short-lived, as a second wave of COVID-19 commenced in late August. Throughout this period, Workplaces, Transit Stations, and Retail sectors exhibited slower recovery trajectories, remaining around -20% throughout much of 2020, reflecting ongoing hesitancy among employees to return to physical office environments.

The emergence of the Delta variant in mid-2021 did not significantly affect mobility patterns, as many mobility variables exhibited a more stable structure. In fact, park mobility notably increased, surpassing all other categories to reach nearly +40%. This surge coincided with summer, when outdoor activities became more appealing, and many travel restrictions were relaxed, facilitating movement. This was followed by a marked increase in mobility during the fall of 2021, driven by widespread vaccine distribution and the gradual lifting of restrictions. By October 2021, categories such as Grocery & Pharmacy and Parks were almost returning back to baseline levels.

The Omicron variant surge at the end of 2021 impacted mobility but to a lesser degree than earlier waves. By December 2021, Workplace mobility experienced a sudden drop to around -25%, likely due to renewed fears surrounding this new variant and associated restrictions. Nonetheless, following February 2022, all mobility variables surpassed baseline levels for the first time since the pandemic began. Throughout this timeline, Residential mobility remained the most consistent variable, maintaining a positive trend with minimal fluctuations, even amidst the emergence of new variants.

Heatmap to show average mobility changes during key events.

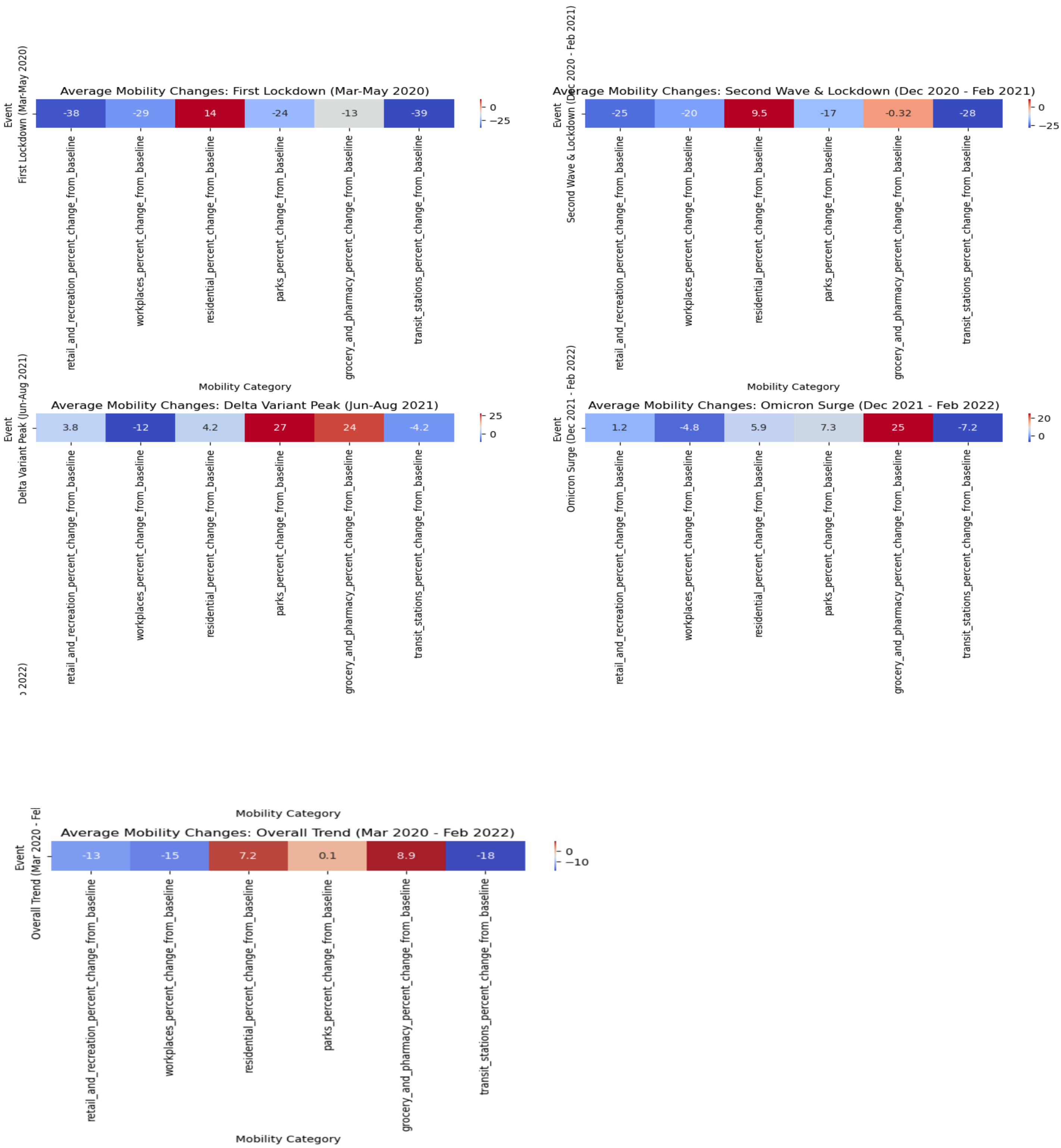


Figure (17): Heatmap showing average mobility changes across key global events related to

Each heatmap depicts the percentage change from baseline levels, highlighting how various sectors responded to the evolving circumstances. During the First Lockdown (Mar-May 2020), mobility declined across all categories except for Residential. The Retail & Recreation sector experienced an average decrease of -38%, reflecting a substantial drop in consumer activity as people were largely confined to their homes. Similarly, the Workplaces category saw a decrease of -29%, indicative of the swift transition to remote/ work from home alongside many redundancies.

In the Second Wave & Lockdown (Dec 2020 - Feb 2021), mobility across all variables showed slight improvement, although Residential mobility decreased by an additional 6%, remaining above baseline levels. This suggests that between the first and second lockdowns, there was generally more mobility during the second wave.

The Delta Variant Peak (Jun-Aug 2021) marked another significant shift, with mobility variables improving substantially. At this point, all mobility categories were above baseline levels, except for Workplaces, which stood at -12%, and Transit Stations, which registered -4.2%.

Finally, the Overall Trend (Mar 2020 - Feb 2022) highlights the cumulative effects of these events. Retail & Recreation, Workplaces, and Transit Stations experienced declines, while Residential and Grocery & Pharmacy sectors saw increases, with Parks remaining relatively stable at 0%.

Average Retail & Recreation Mobility Changes During Key Events

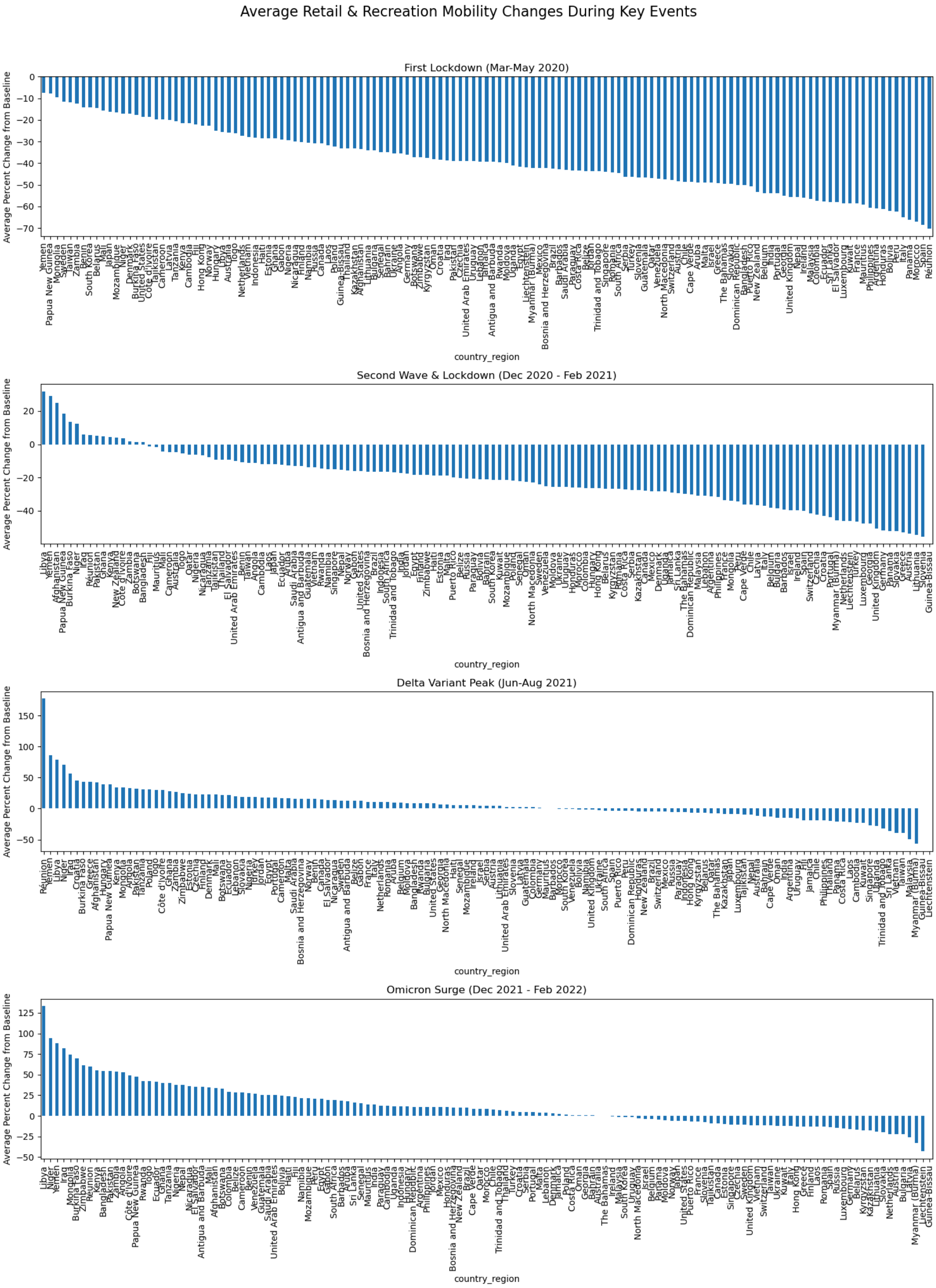
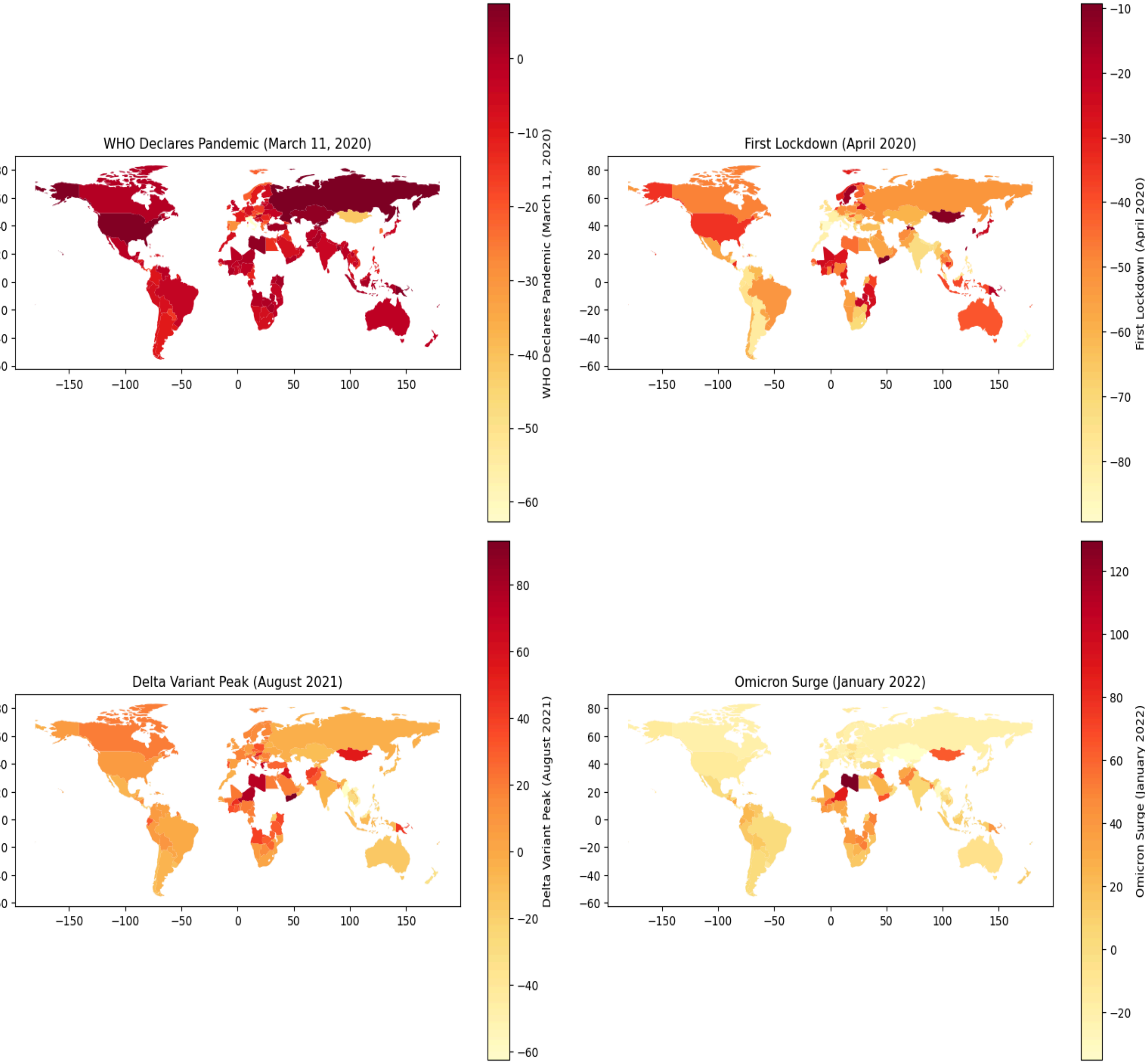


Figure (18): Bar plots that illustrate the average mobility changes in the Retail & Recreation category across several critical global events during the COVID-19 pandemic.



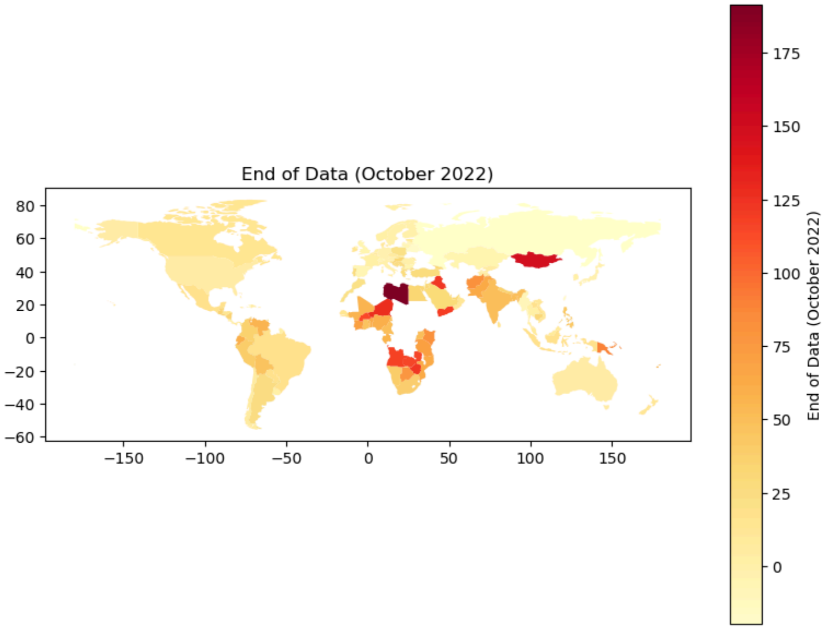


Figure (19): Choropleth map of retail and recreation mobility changes during significant events in the COVID-19 pandemic

During the First Lockdown (March-May 2020), countries like Italy and Spain experienced drastic mobility declines, almost reaching -70%. This severe reduction can be attributed to stringent lockdown measures imposed by their governments in response to rising COVID-19 cases, coupled with widespread public fear of the virus. Specifically, Italy's rapid rise in infection rates prompted some of the first extensive lockdown measures in Europe ("Italy, the first country in Europe to enter lockdown, starts to emerge," n.d.), significantly impacting daily activities and mobility patterns. In contrast, Mongolia witnessed a mobility decline of less than -10%. This resilience is largely due to early lockdown measures implemented in January 2020, motivated by Mongolia's geographical proximity to China, which enabled a swift governmental response to the threat posed by the virus.

Moving into the Second Wave & Lockdown (December 2020 - February 2021), mobility levels remained low across many countries. However, the UK reported a mobility drop below -40%, reflecting the impact of renewed lockdown measures during the winter months when cases surged. The Delta Variant Peak (June-August 2021) revealed a stark contrast in mobility patterns: while Yemen and Libya experienced mobility increases exceeding +50%, Singapore faced reductions of -10%. The increases in Libya can be attributed to a significant influx of internal displacement and refugee flows due to the ongoing civil conflict, which contributed to a more mobile population.

During the Omicron Surge (December 2021 - February 2022), similar trends emerged, as seen during the Delta Variant phase, with Libya showcasing mobility levels surpassing 125%. This surge highlights the continued volatility in mobility patterns influenced by both local conditions and international events, including civil unrest. From 2020 to 2021, Libya had a retail change of 81.04%, making it the country with the largest increase, while Mongolia followed closely behind with a change of 77.69% from 2021 to 202. By the End of Data in October 2022, the final map indicates a general recovery trend in North America and Western Europe, although regions in Africa and South Asia remained darker, reflecting higher mobility.

Average Workplaces Mobility Changes During Key Events

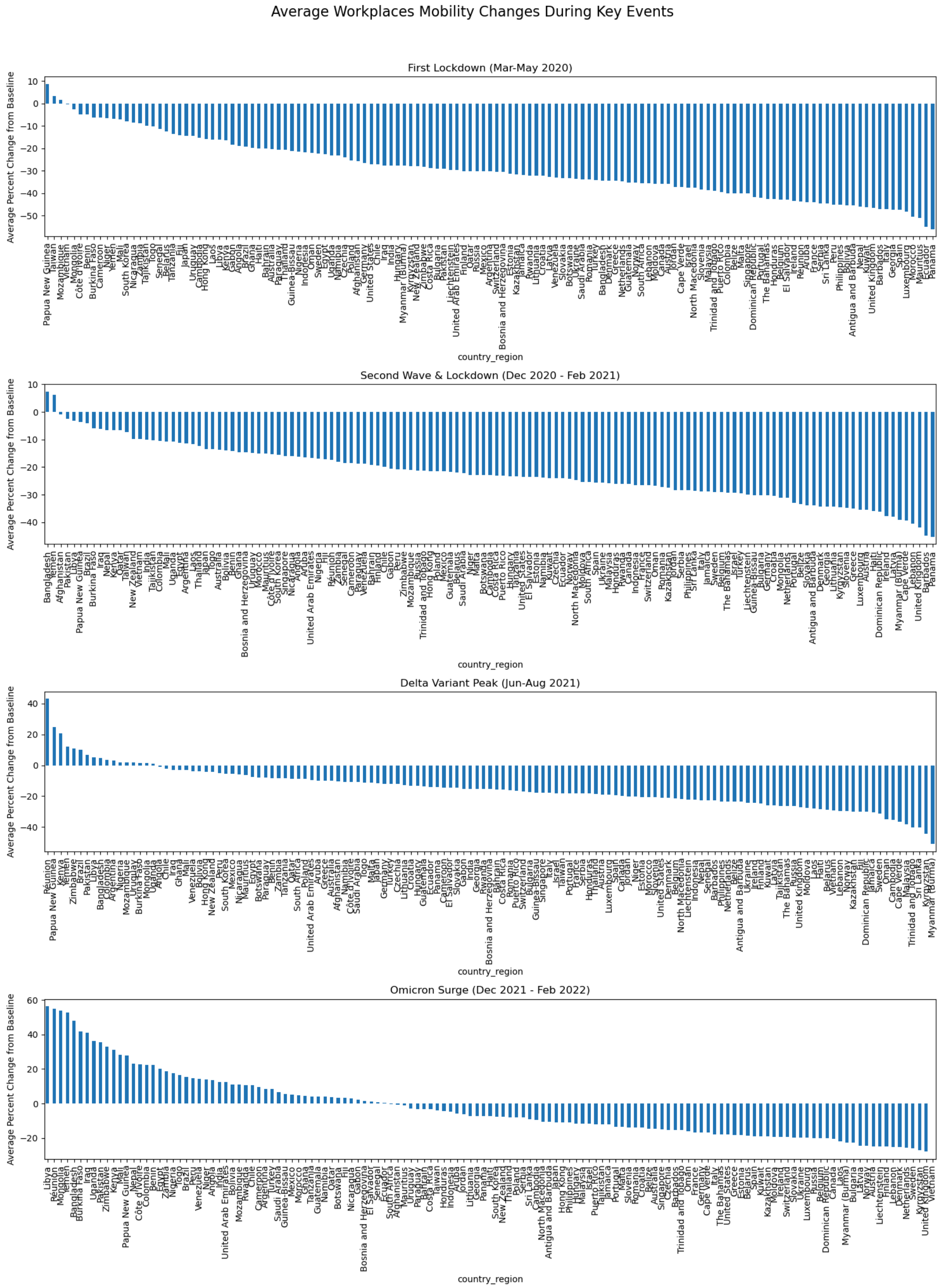
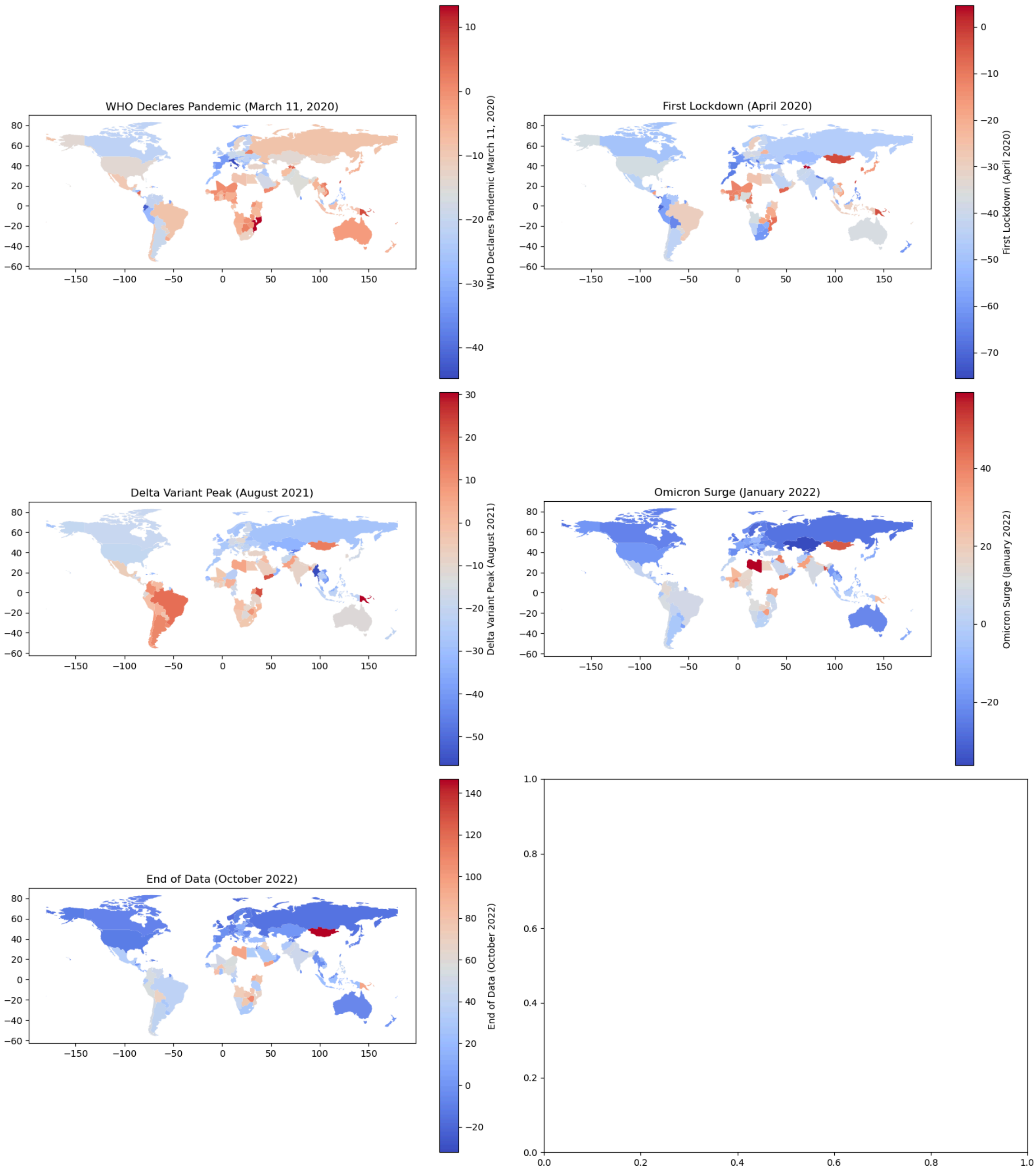


Figure (20): Bar plots illustrating average workplace mobility changes across key global events.



Figure(21): choropleth map of key events for workplace mobility

The bar plots illustrate significant declines in workplace mobility during critical events, particularly the First Lockdown (March-May 2020), which resulted in widespread reductions across many countries. For example, the United Kingdom saw workplace mobility plummet by over -40% due to the closure of many businesses and work-from-home schemes. In fact, in April 2020, 46.6% of people employed in the UK did some work from home (“Coronavirus and homeworking in the UK - Office for National Statistics,” n.d.), driven by stringent restrictions aimed at curbing the rapid spread of COVID-19, which was particularly severe in urban centres like London. Conversely, during this period, Bangladesh experienced a remarkable increase in workplace mobility, attributed to its reliance on informal economies, where a significant portion of the population engaged in daily labour to support their livelihoods. Furthermore, the high population density and the predominance of informal work arrangements necessitated a swift return to work despite ongoing health risks.

During the Second Wave (December 2020 - February 2021), mobility levels remained low in many countries. For instance, Panama faced a decline exceeding -40% due to continued lockdown measures and high case numbers.

In stark contrast, Bangladesh managed to sustain a rise in mobility, demonstrating a different approach to public health and economic activity. This resilience was highlighted by a report on Bangladesh employment during COVID-19, indicating that "the pandemic has resulted in a 20% increase in the number of those working fewer than 40 hours per week" (Hossain et al., 2023)

The Delta Variant Peak (June-August 2021) again led to reductions in mobility, but the declines were less severe compared to earlier phases, with noticeable upticks in some regions, including South America, Africa and parts of Asia.

Average Residential Mobility Changes During Key Events

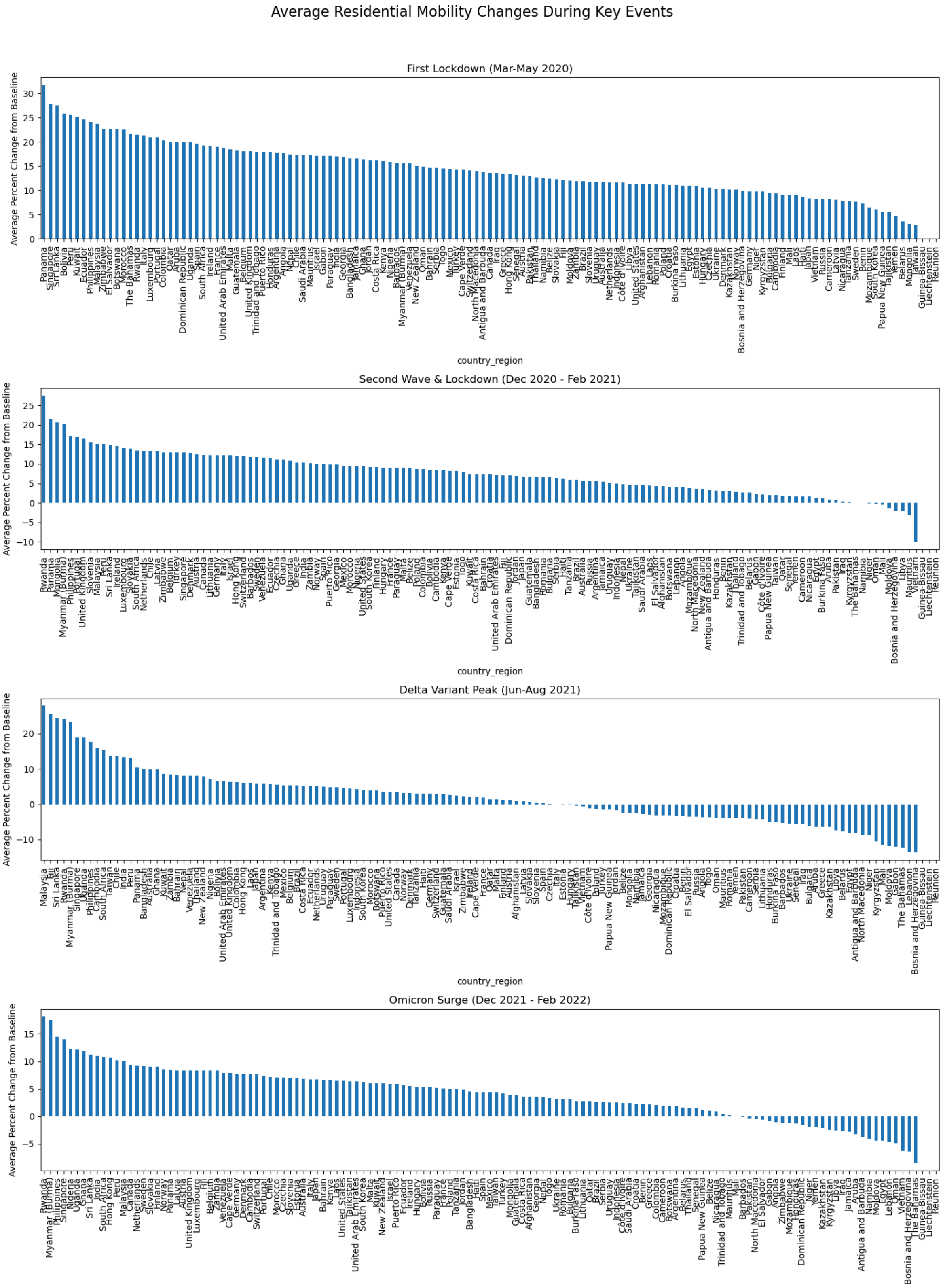
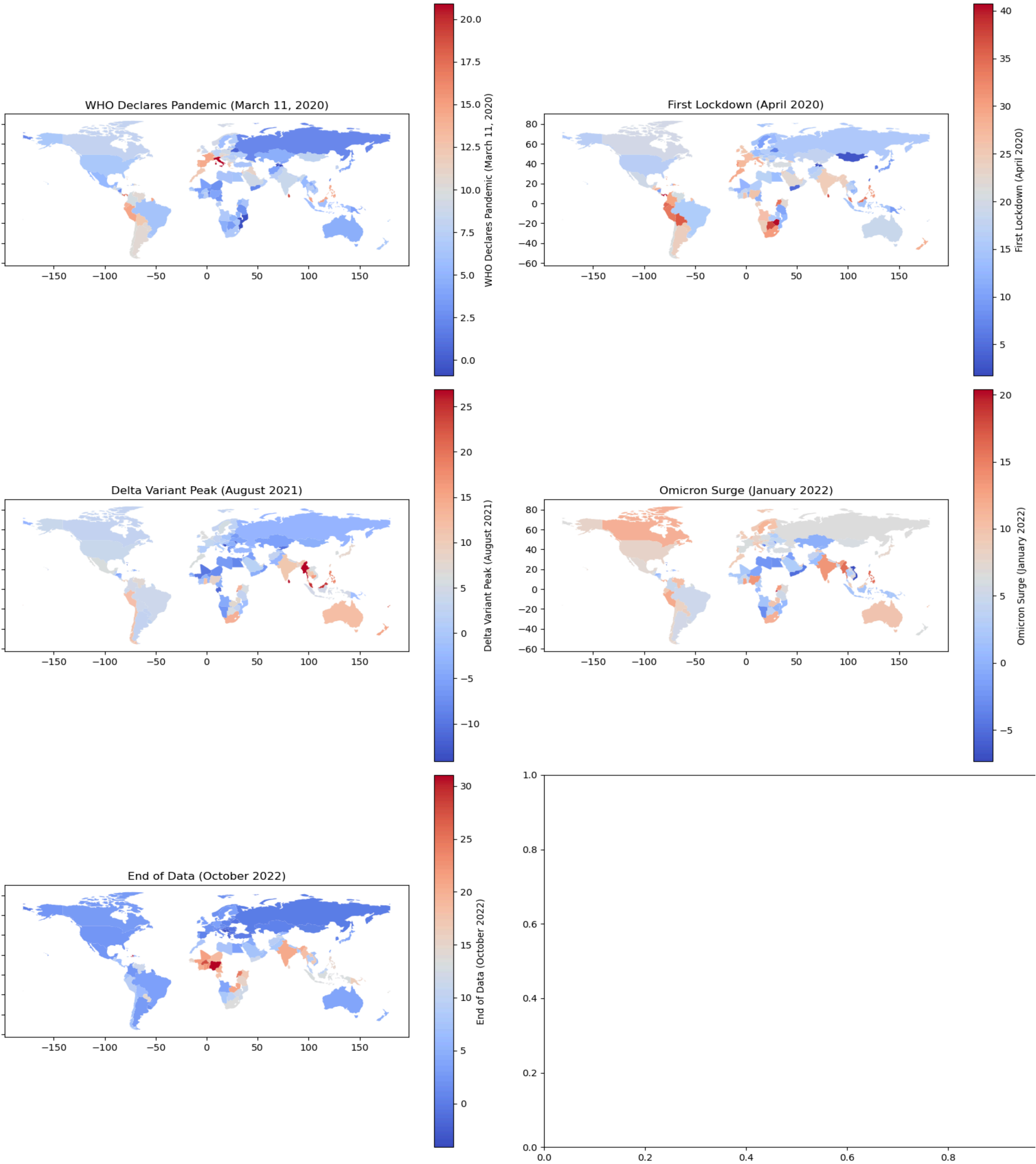


Figure (22): Bar plots illustrating average residential mobility changes across countries during key global events



Figure(23): choropleth map of residential percentage change

On March 11, 2020, countries such as Italy experienced a significant decline of -44.88% in residential mobility, contrasting with Mozambique and Panama, which saw increases of 13.38% and 17.94%, respectively. The First Lockdown in April 2020 highlighted Panama's remarkable rise of 40.75%, while Tajikistan faced a slight decline of 1.70%. Panama’s rise in residential mobility can be attributed to the strict measures in place, such as separating men and women from leaving the house for only 2 hours a day on different days. (“Coronavirus,” 2020)

During the Delta Variant Peak in August 2021, Myanmar maintained a notable increase of 26.89%, while Lebanon recorded a drop of -14.16%. The Omicron Surge in January 2022 showcased Rwanda's significant rise of 20.40%, juxtaposed against Vietnam's decline of -7.36%. By the end of data in October 2022, Haiti had emerged with a substantial increase of 31.05%, reflecting a recovery phase.

Analysing the absolute differences, countries like Mali and Burkina Faso recorded impressive changes of 26.29% and 23.67%, respectively, from 2021 to 2022, while the United Kingdom and Malaysia experienced declines of -4.44% and -5.89%, respectively. Looking at the world map, it's clear that residential had a very negligible fall; most regions experienced heightened residential; this can be attributed to the varying restrictions in place mandating the public to stay at home for most of the pandemic.

Average Parks Mobility Changes During Key Events

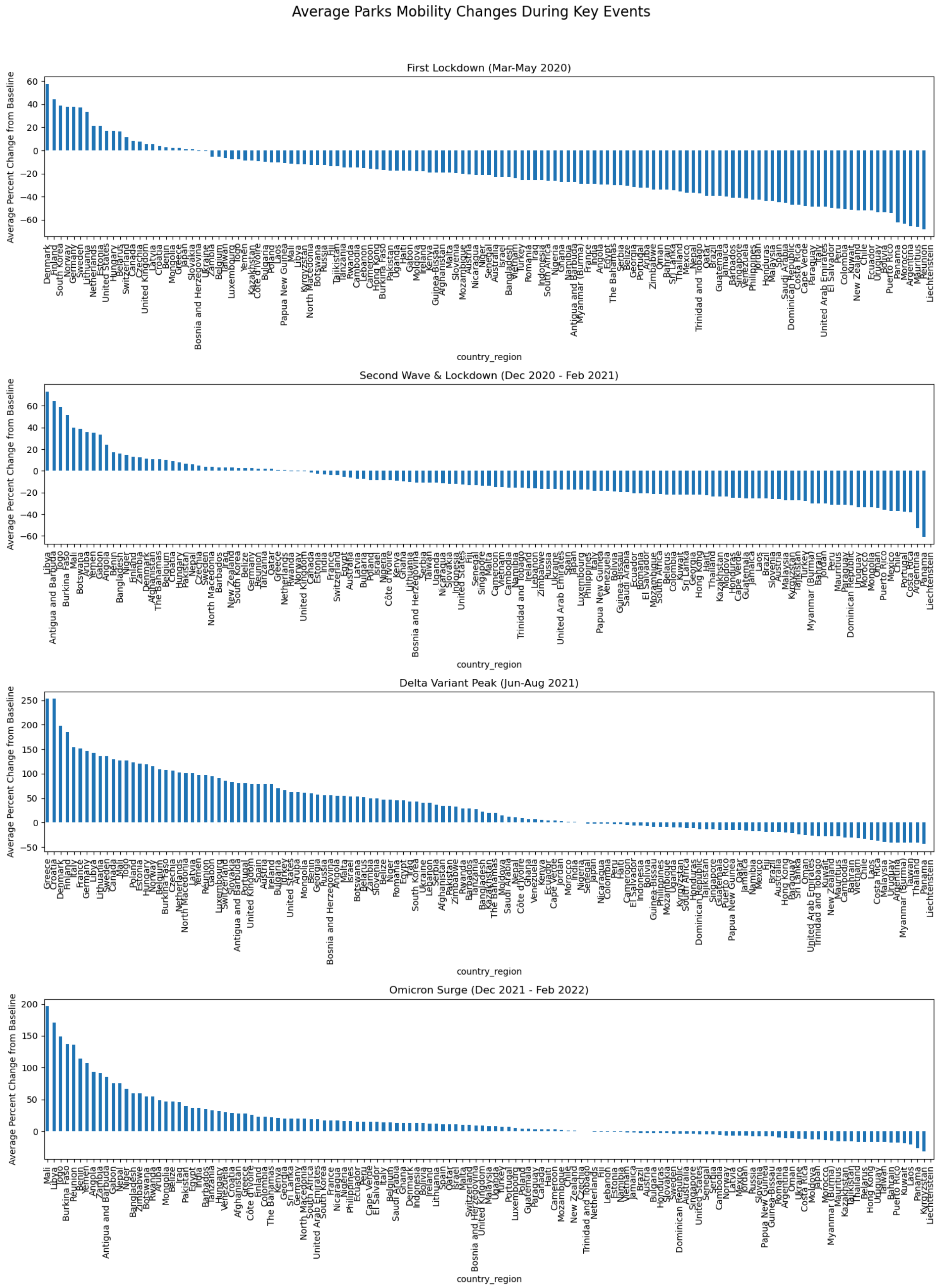
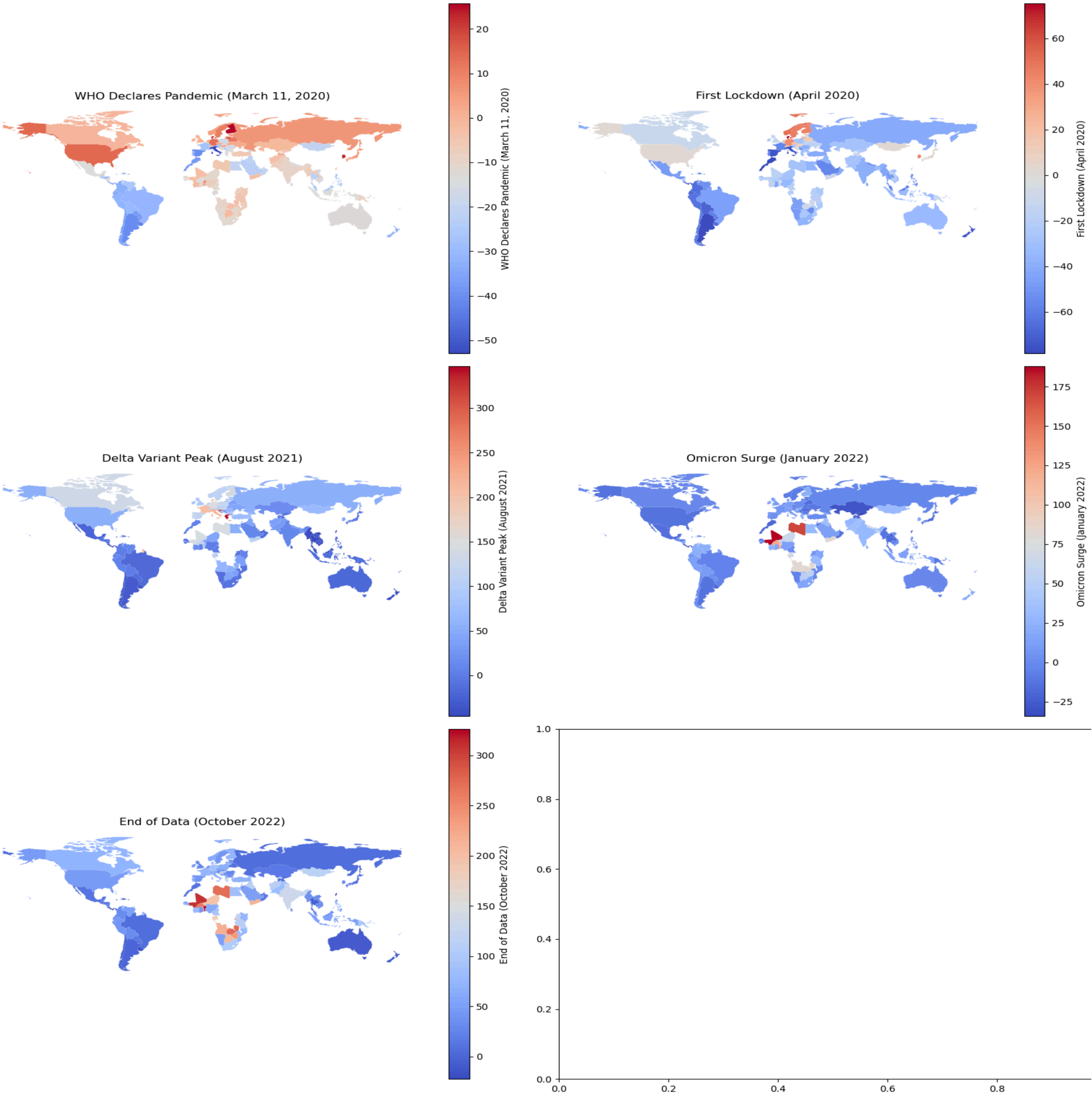


Figure (24): Bar plots illustrating average park mobility changes during key events



Figure(25): choropleth map of parks mobility change

Initially, with the WHO declaring the pandemic on March 11, 2020, countries like Finland and South Korea saw notable increases in park mobility, with changes of 25.73% and 23.19%, respectively. This was credited to South Korea's effective measures of trying to halt the impact of the pandemic. Unlike most countries, South Korea abstained from implementing a full lockdown. The government gave the freedom to the public to choose whether to go out or not. A study which analysed the impact of pandemic fear and visitation to parks in Seoul found that people who had a greater fear of the pandemic spent more time at parks (Choi, 2024). By August 2021, during the Delta Variant Peak, Greece showcased an exceptional increase of 347.01%, yet Thailand reported a significant decline of -46.00%. The Omicron Surge in January 2022 continued to highlight these patterns, with Mali and Libya leading in positive changes, while Kyrgyzstan recorded a decrease of -34.29%. By the end of 2022, countries like Benin and Mali demonstrated remarkable recoveries in park mobility, with increases of 326.33% and 308.82%, respectively.

Average Grocery & Pharmacy Mobility Changes During Key Events

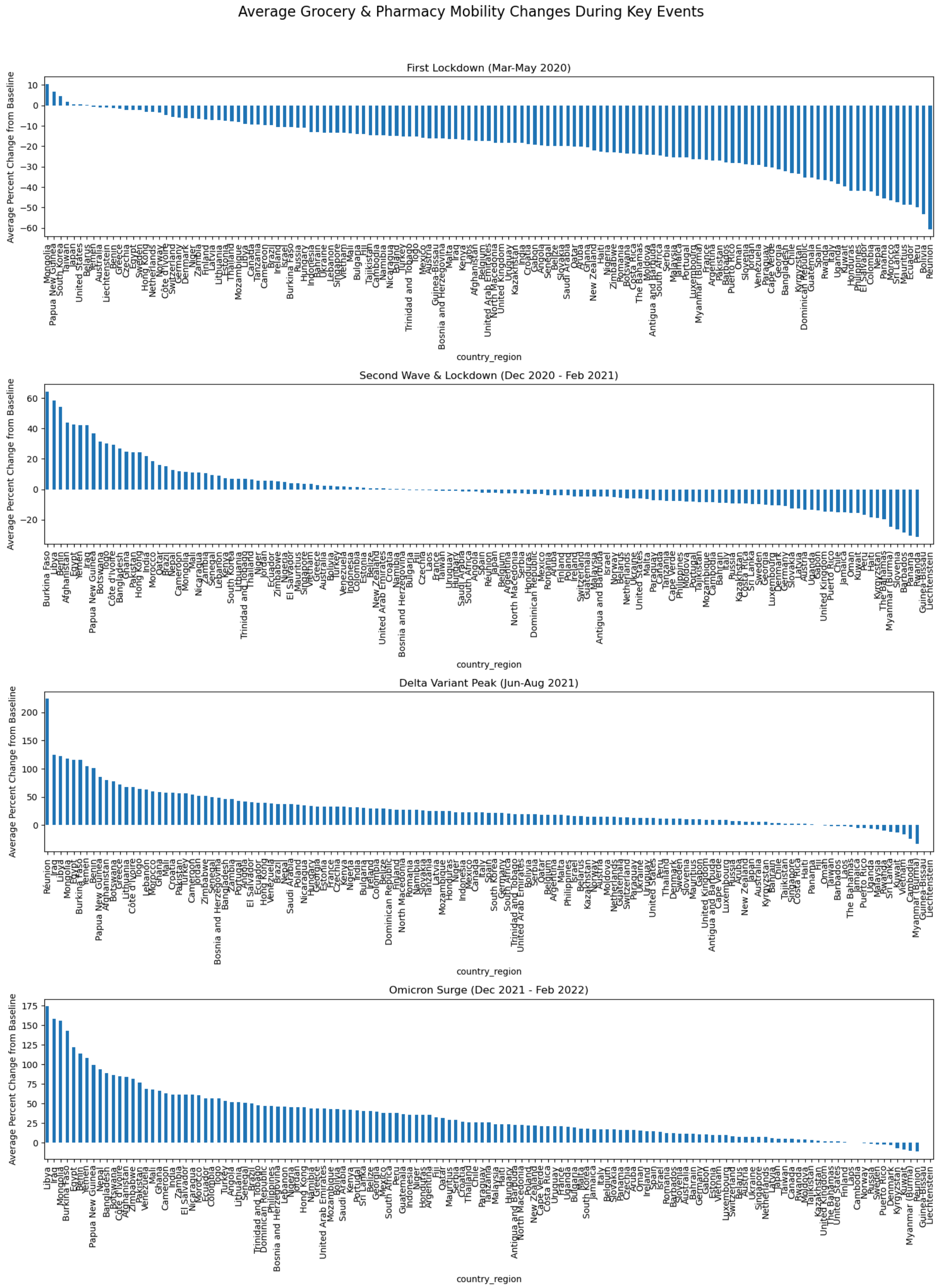
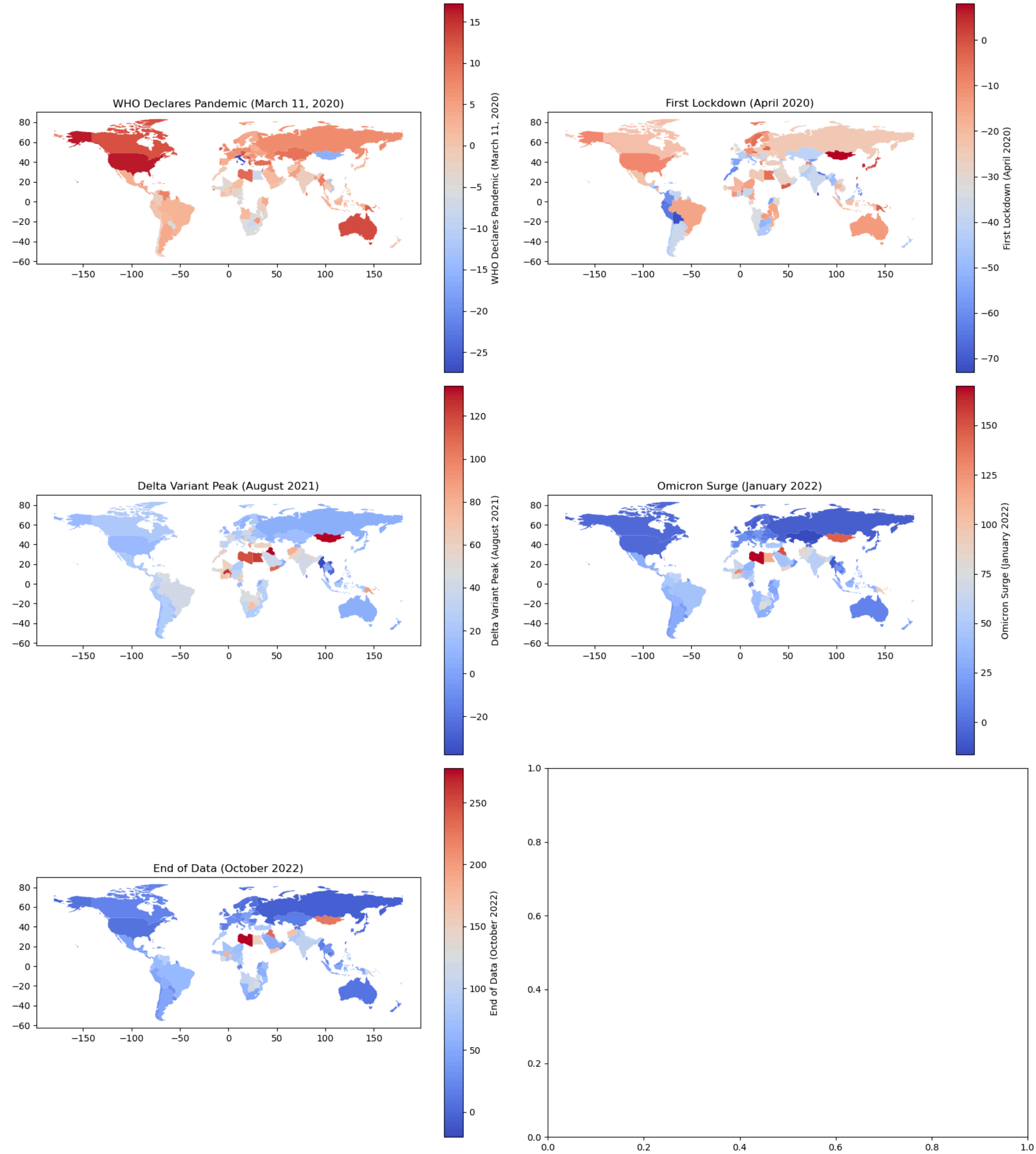


Figure (26): Average Grocery & Pharmacy Mobility Changes During Key Events

During the First Lockdown, there was a notable increase in Grocery and pharmacy mobility, with some countries experiencing over 30% positive change, likely due to panic buying and stockpiling of essentials. Conversely, the Second Wave & Lockdownsaw a decline, with countries like Spain and the UK reporting significant reductions in mobility, reflecting the stricter restrictions. The Delta Variant Peak indicated an overall recovery, with countries such as France showing improved mobility rates. However, the Omicron Surge resulted in varied impacts, where the average mobility saw a resurgence again, suggesting increased consumer confidence despite the surge in cases.



Figure(27): choropleth map of grocery and pharmacy mobility

From 2020 to 2021, Libya saw the most significant increase in grocery and pharmacy mobility, surging by 104%, closely followed by Iraq with a 103% rise. Notably, most of the countries experiencing these increases are classified as Least Developed Countries (LDCs). Countries classified as Least Developed Countries (LDCs) often have a higher dependency on local markets for food and essentials, prompting a rapid rebound in mobility as consumers resume shopping activities. The combination of early lockdowns that led to panic buying and the subsequent easing of restrictions allowed for increased movement toward grocery stores as people sought to stock up on necessities while balancing the ongoing challenges posed by the pandemic. In contrast, Myanmar experienced the largest decline at -11.42%. From 2021 to 2022, Libya continued to lead with a further increase of 107.79%, while Russia faced the most considerable drop at -7.65%. From the world map, there was, in fact, high grocery and pharmacy mobility around the world, except for Italy and Mongolia during the declaration of the pandemic. This can be explained by the fact that Italy and Mongolia were amongst the first countries to go into lockdown. The declaration of COVID-19 caused the public to panic and panic buy. Over each development time, the grocery and pharmacy returned to near baseline levels, suggesting increased consumer confidence over the course of the pandemic.

Average Transit Stations Mobility Changes During Key Events

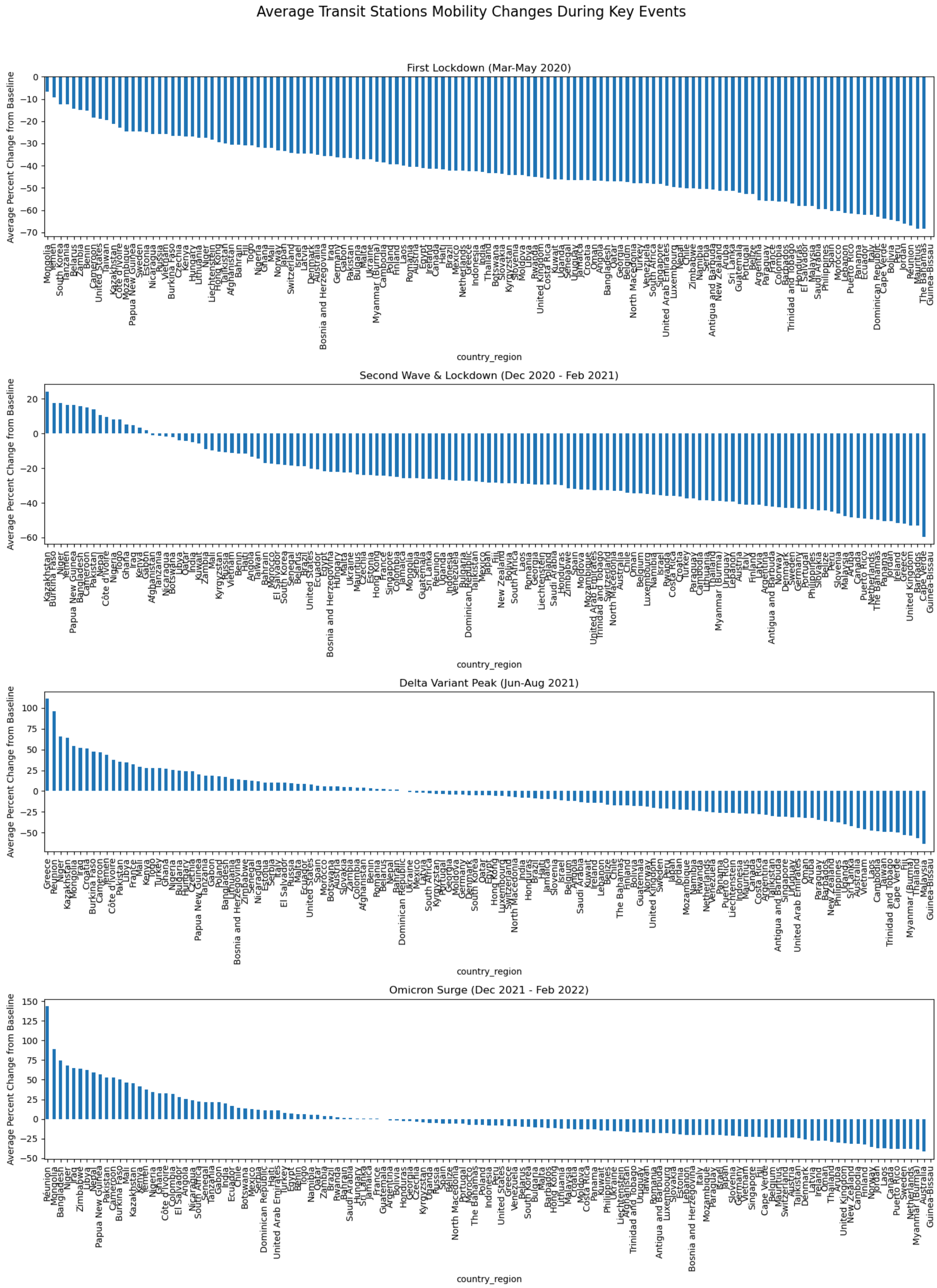
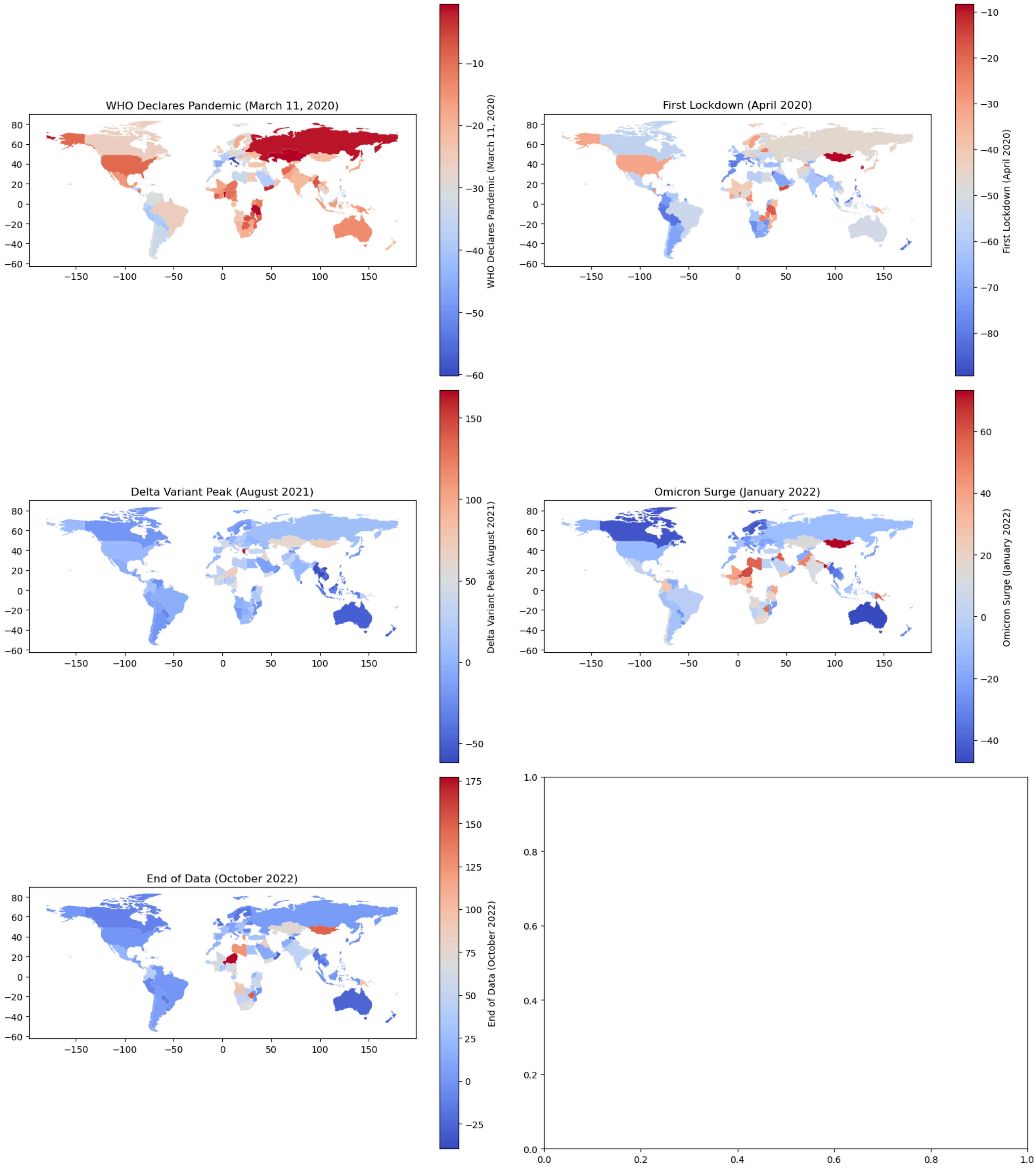


Figure (28): Average Transit Stations Mobility Changes During Key Events.

During the First Lockdown, transit station mobility drastically decreased, with many countries experiencing reductions of around -70%, reflecting strict lockdown measures. The Second Wave also saw a notable decline, with many countries remaining below baseline levels. However, during the Delta Variant Peak, some countries experienced a slight recovery, while the Omicron Surge led to another significant drop in mobility, with more regions seeing a decline than an increase hereafter; this could also be attributed to less workplace mobility. Since fewer people are travelling to work, it means less use of transport. It was reported that public transport usage fell by 50-90% worldwide (The, 2024).



Figure(29): choropleth map of transit stations mobility

The maps illustrate significant changes in transit station mobility across various regions during key pandemic events. In Europe, countries like Italy and Spain experienced dramatic declines in mobility, with reductions of -60.23% and -45.27%, respectively, as they faced stringent lockdowns and rising COVID-19 cases. Conversely, nations in Africa, such as Niger and Libya, showed notable increases in transit station mobility, with changes of 177.25% and 125.33% by October 2022.

From March 2020, countries such as Finland and South Korea saw minimal declines, while other countries like Puerto Rico and Lebanon faced drastic reductions in mobility, illustrating the disparity in responses across different regions. For example, Finland had a relatively small decline of -0.55%, while Puerto Rico's mobility dropped by nearly -46.53%. The absolute changes from 2020 to 2021 reveal that Libya had the largest increase in transit station mobility at 60.30%, highlighting a significant increase from baseline, while Laos experienced a notable decline of -19.91%.

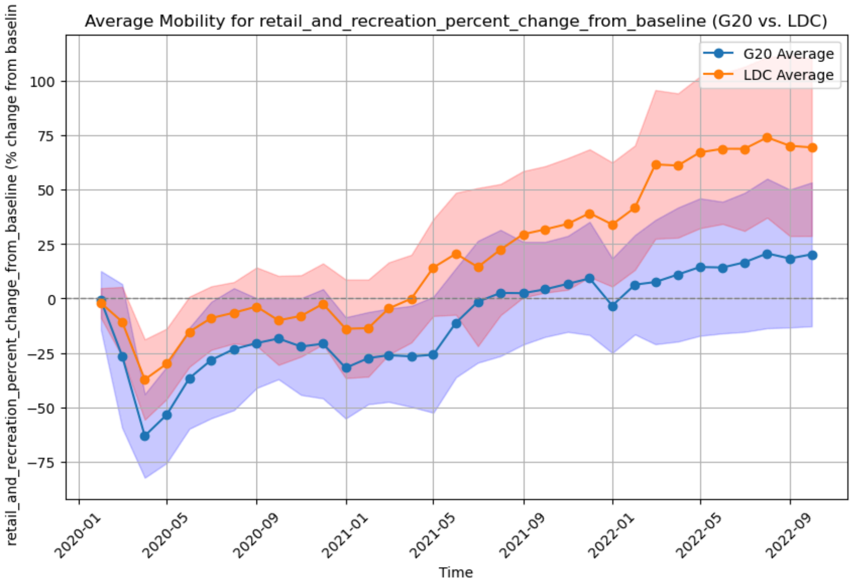
Monthly Mobility Changes Across Continents

Figure(30): Line graphs illustrating monthly changes in mobility across continents

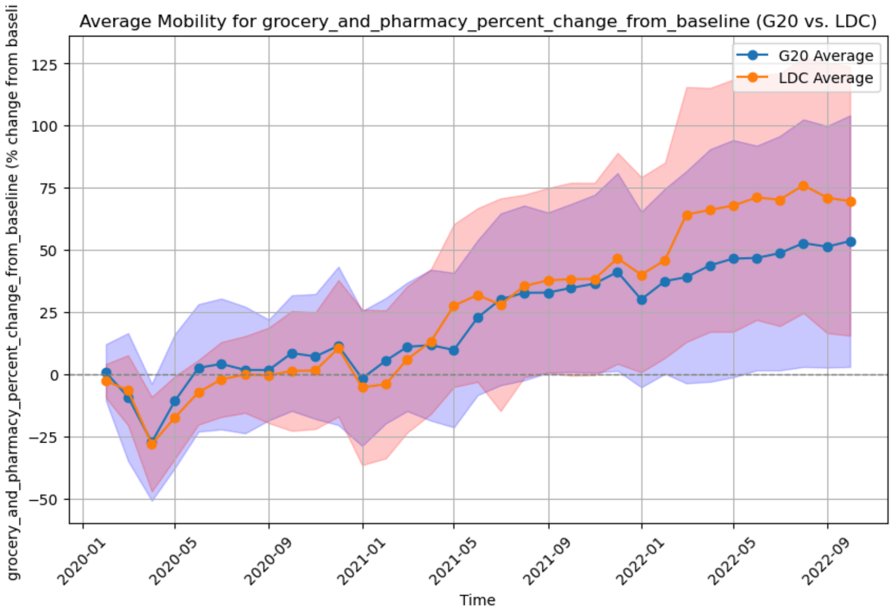
In Europe, notable peaks are observed across all mobility variables, particularly in parks and retail sectors, suggesting a rebound in outdoor activities and consumer behaviour following the lifting of lockdown measures. Three distinct peaks emerge in park mobility: the first in mid-2020 coincides with initial lockdown relaxations, the second around the holiday season in 2021, and the third in summer 2022, indicating a strong public inclination towards outdoor spaces during favourable conditions. North America mirrors this trend but to a lesser extent, particularly in parks and retail mobility, with spikes reflecting seasonal changes and pandemic-related policy shifts.

Conversely, Africa displays a more stable recovery with a particular spike in early 2021 and higher average mobility levels across variables. Mobility is also quite similar in Asia to that in Africa. South America showed an average positive trajectory in terms of mobility after November 2020. Meanwhile, Oceania seems to be the worst hit, with some variables still below baseline levels.

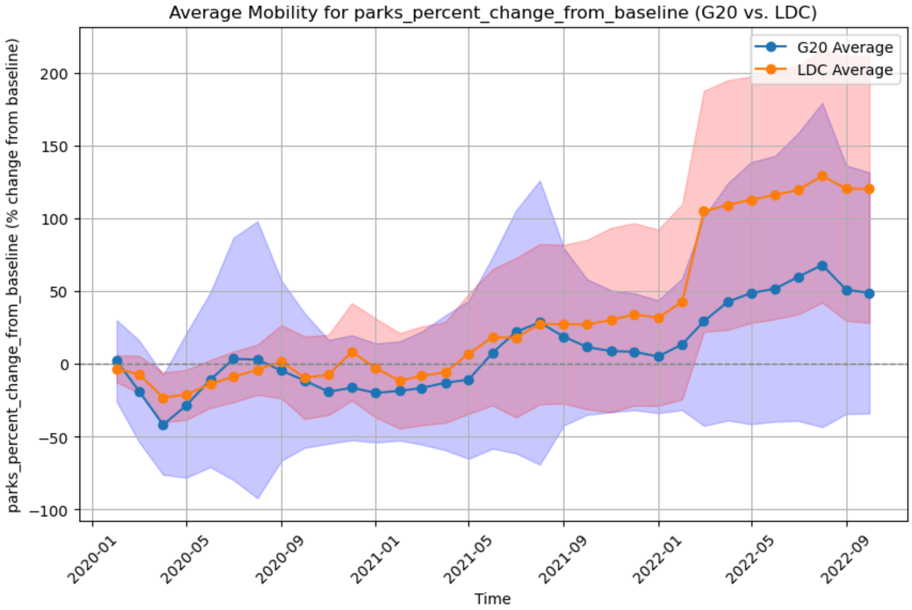
G20 and LDC comparison



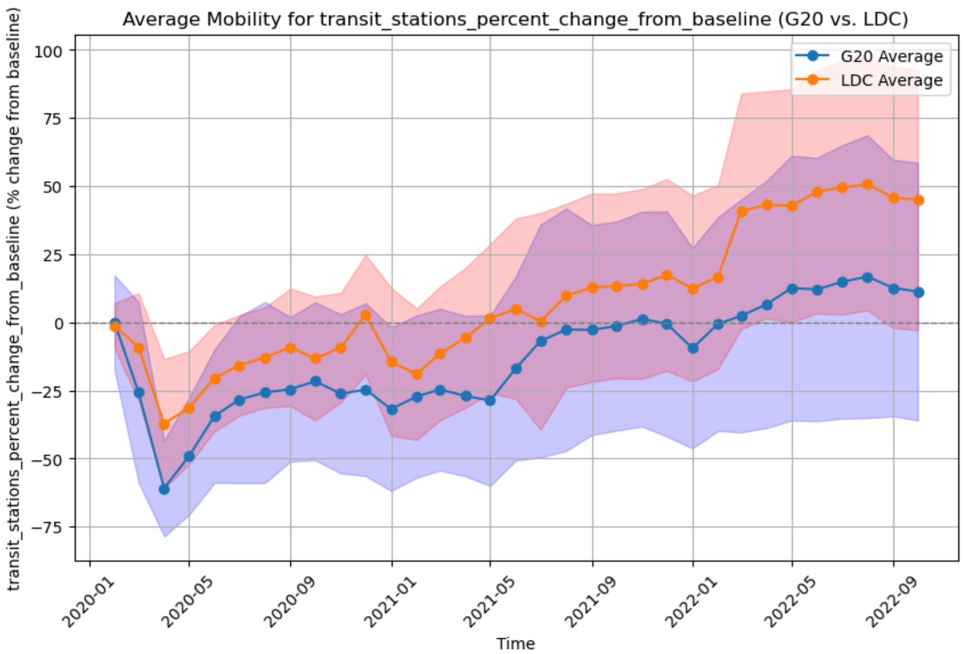
Figure(31a): Line graphs of average G20 and LDC mobility during key periods



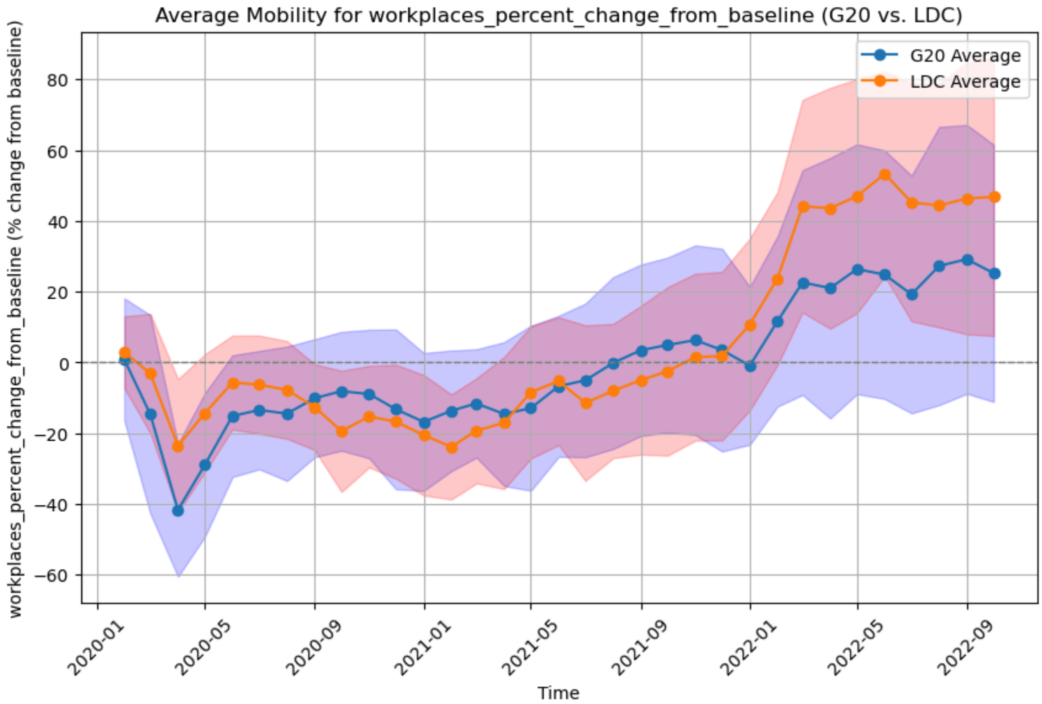
Figure(31b): Line graphs of average G20 and LDC mobility during key periods



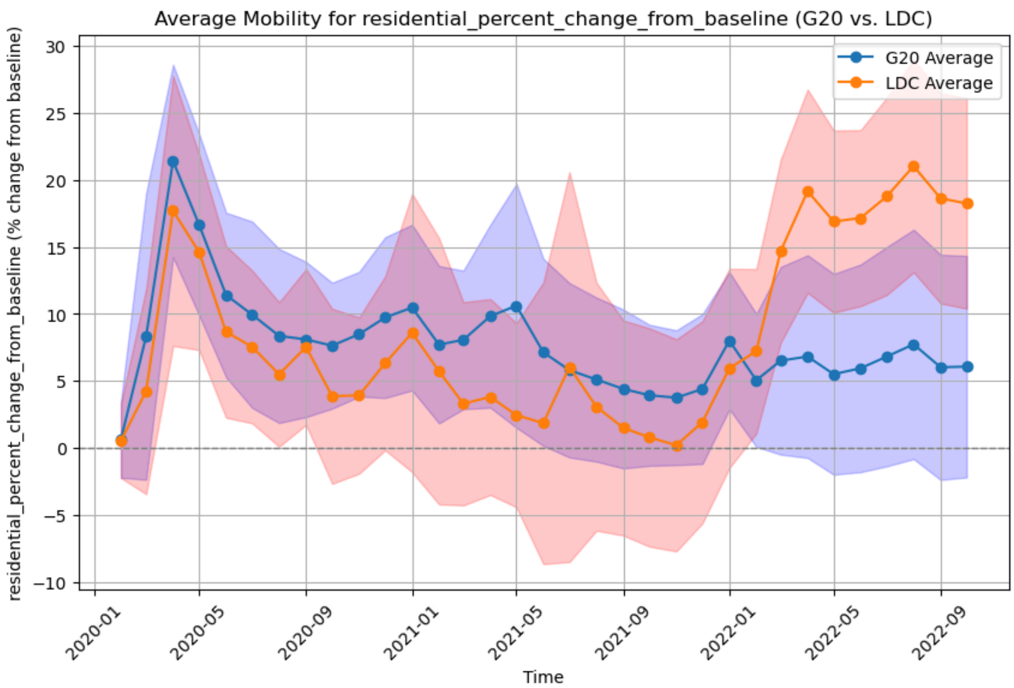
Figure(31c): Line graphs of average G20 and LDC mobility during key periods



Figure(31d): Line graphs of average G20 and LDC mobility during key periods



Figure(31e): Line graphs of average G20 and LDC mobility during key periods



Figure(31f): Line graphs of average G20 and LDC mobility during key periods

The first graph illustrates the average mobility changes for retail and recreation. The G20 countries are depicted by the blue line, showing a significant decline in mobility during the early months of the pandemic, followed by a gradual recovery. By mid-2021, G20 countries had stabilised around the baseline level. In contrast, LDC countries, represented by the orange line, experienced a similar drop in mobility but to a lesser extent but displayed a faster recovery rate.

The second graph focuses on changes in grocery and pharmacy mobility. Both groups had very similar mobility levels; however, after 2022, LDC mobility significantly increased.

The third graph details the changes in mobility for parks. Similar to grocery and pharmacy, mobility was head to head; however, mobility skyrocketed for LDCs, exceeding 100% compared to g20 countries, which remained just below 75%.

The fourth graph showcases mobility changes for transit stations. LDCs had higher mobility. However, the fluctuations remained the same.

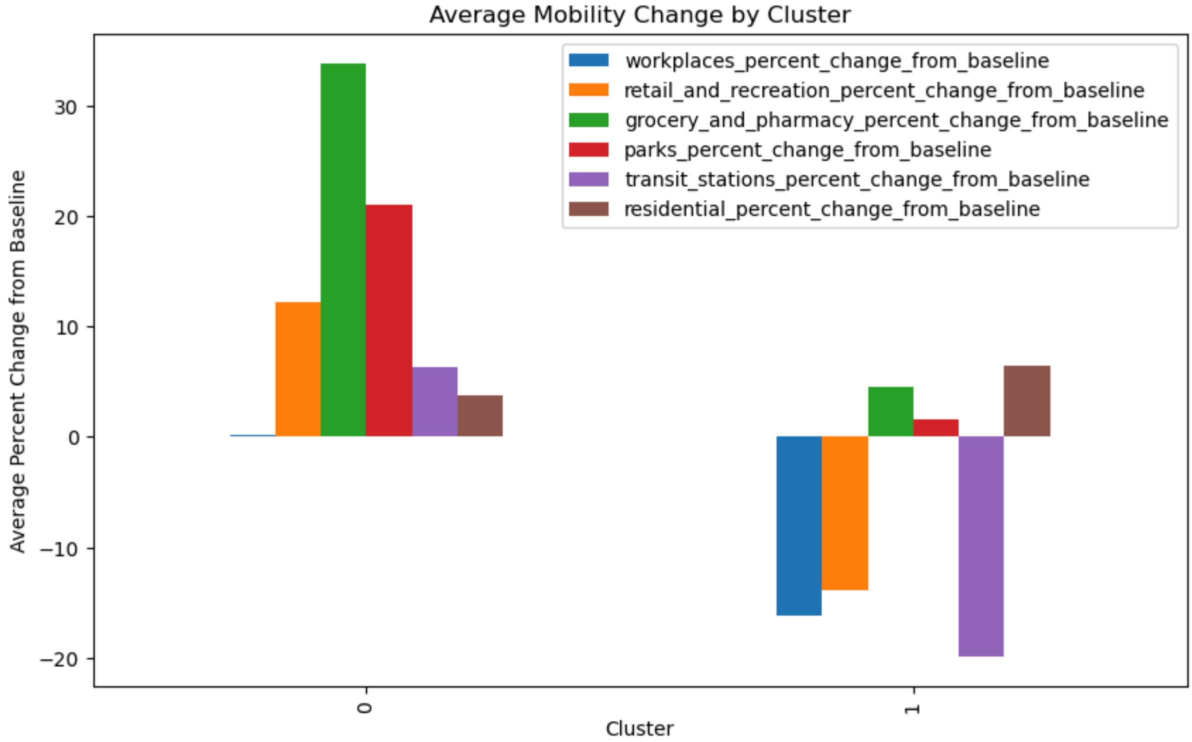
Workplace mobility G20 faced greater declines exceeding -40%. Initially recovering better than LDC, in January 2022, LDCs took charge.

Residential, both groups had a massive rise, followed by a sudden decline. Throughout time, levels remained above baseline. With G20 above, however, January 2022 LDCs had a massive spike, exceeding G20 by a milestone.

In summary, LDC countries tend to show quicker recoveries across all mobility categories compared to G20 countries. The trends illustrate that while both groups experienced initial declines in mobility due to the pandemic, LDC countries rebounded faster and achieved stability sooner. In contrast, G20 countries have faced continued mobility challenges, with their recovery trailing behind that of LDC countries. This discrepancy underscores the varying capacities and responses to the pandemic between economically advanced and developing nations.

4.3 Mobility Pattern Analysis - K means clustering

Average Mobility Change by Cluster



Figure(32): Bar chart of average per cent change from baseline for different mobility variables across clusters identified in the K-means clustering analysis.

The notable differences between the two clusters reveal significant insights into the mobility patterns of the countries within each group. Cluster 0 exhibits positive mobility across all variables, particularly in grocery, pharmacy, and parks, which exceeds +30% during key time periods. The countries in this cluster, primarily comprising LDCs and developing nations like Afghanistan, Angola, and Burkina Faso, are experiencing a robust recovery. Conversely, Cluster 1 shows very low positive mobility, with some variables exceeding -10%, suggesting that these countries, which include a mix of developed economies like Australia and Germany as well as emerging markets such as Brazil and India, are struggling to recover from COVID-19's impacts. Overall, these patterns illustrate that Cluster 0 countries are characterised by resilience and recovery, while Cluster 1 countries face significant hurdles that impede their mobility and economic activity.

```
Countries in Cluster 0: ['Afghanistan' 'Angola' 'Bangladesh' 'Benin' 'Botswana' 'Burkina Fa
so'
 'Cameroon' "Côte d'Ivoire" 'Egypt' 'Ghana' 'Iraq' 'Kenya' 'Libya' 'Mali'
 'Mongolia' 'Nicaragua' 'Niger' 'Nigeria' 'Pakistan' 'Papua New Guinea'
 'Tanzania' 'Togo' 'Yemen' 'Zambia' 'Zimbabwe']
Countries in Cluster 1: ['Argentina' 'Australia' 'Austria' 'Bahamas' 'Belarus' 'Belgium' 'B
elize'
 'Bolivia' 'Bosnia and Herz.' 'Brazil' 'Bulgaria' 'Cambodia' 'Canada'
 'Chile' 'Colombia' 'Costa Rica' 'Croatia' 'Czechia' 'Denmark'
 'Dominican Rep.' 'Ecuador' 'El Salvador' 'Estonia' 'Fiji' 'Finland'
 'France' 'Gabon' 'Georgia' 'Germany' 'Greece' 'Guatemala' 'Haiti'
 'Honduras' 'Hungary' 'India' 'Indonesia' 'Ireland' 'Israel' 'Italy'
 'Jamaica' 'Japan' 'Jordan' 'Kazakhstan' 'Kuwait' 'Kyrgyzstan' 'Laos'
 'Latvia' 'Lebanon' 'Lithuania' 'Luxembourg' 'Malaysia' 'Mexico' 'Moldova'
 'Morocco' 'Mozambique' 'Myanmar' 'Namibia' 'Nepal' 'Netherlands'
 'New Zealand' 'North Macedonia' 'Norway' 'Oman' 'Panama' 'Paraguay'
 'Peru' 'Philippines' 'Poland' 'Portugal' 'Puerto Rico' 'Qatar' 'Romania'
 'Russia' 'Rwanda' 'Saudi Arabia' 'Senegal' 'Serbia' 'Slovakia' 'Slovenia'
 'South Africa' 'South Korea' 'Spain' 'Sri Lanka' 'Sweden' 'Switzerland'
 'Taiwan' 'Tajikistan' 'Thailand' 'Trinidad and Tobago' 'Turkey' 'Uganda'
 'Ukraine' 'United Arab Emirates' 'United Kingdom'
 'United States of America' 'Uruguay' 'Venezuela' 'Vietnam']
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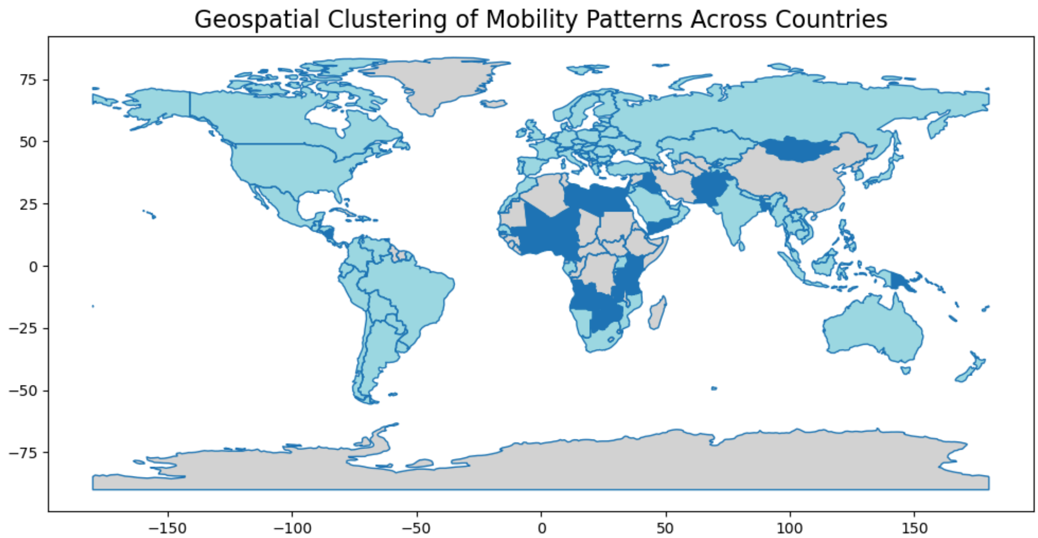
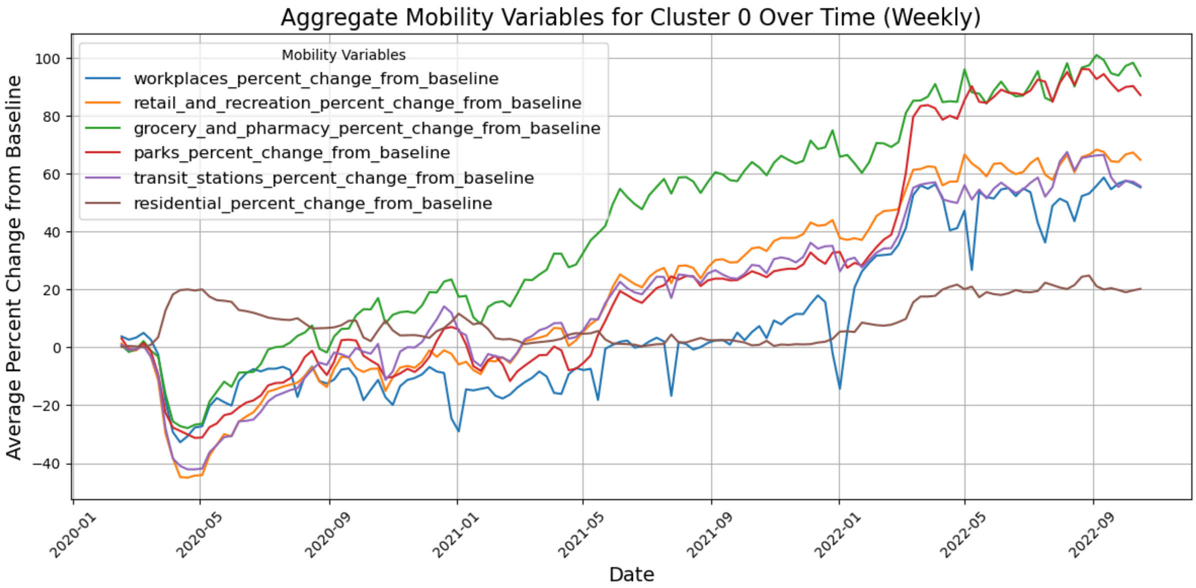
Figure(33): List of countries assigned to each cluster

Geospatial Clustering of Mobility Patterns Across Countries

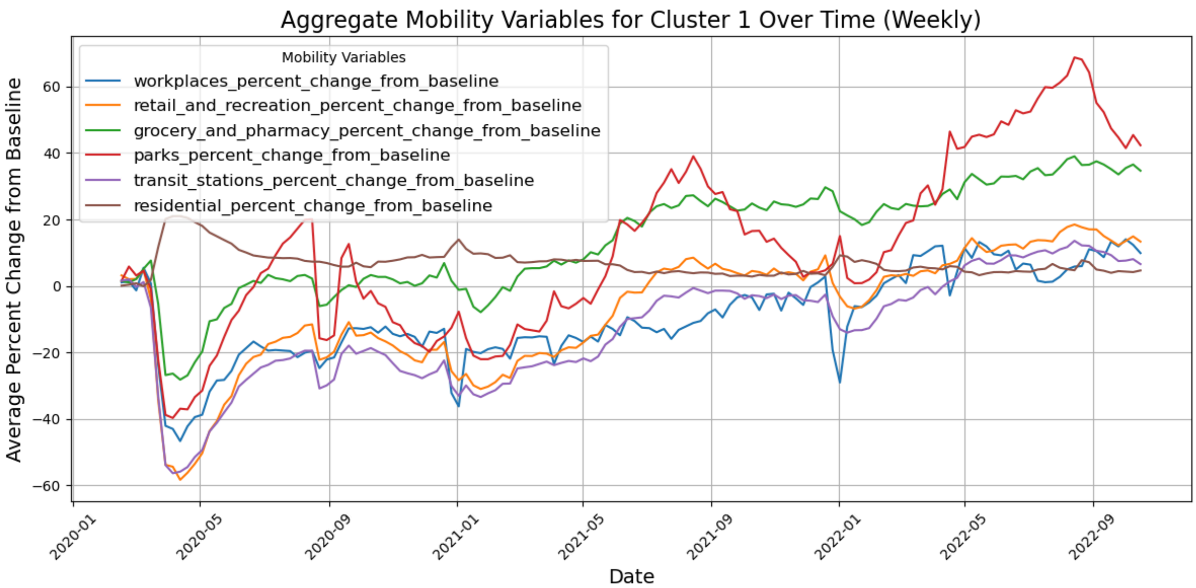


Figure(34): Geospatial distribution of mobility clusters identified through clustering analysis.

Aggregate Mobility Variables for Cluster 0 Over Time (Weekly)



Figure(35a): line graph of clustering aggregate of all mobility variables over time Cluster 0



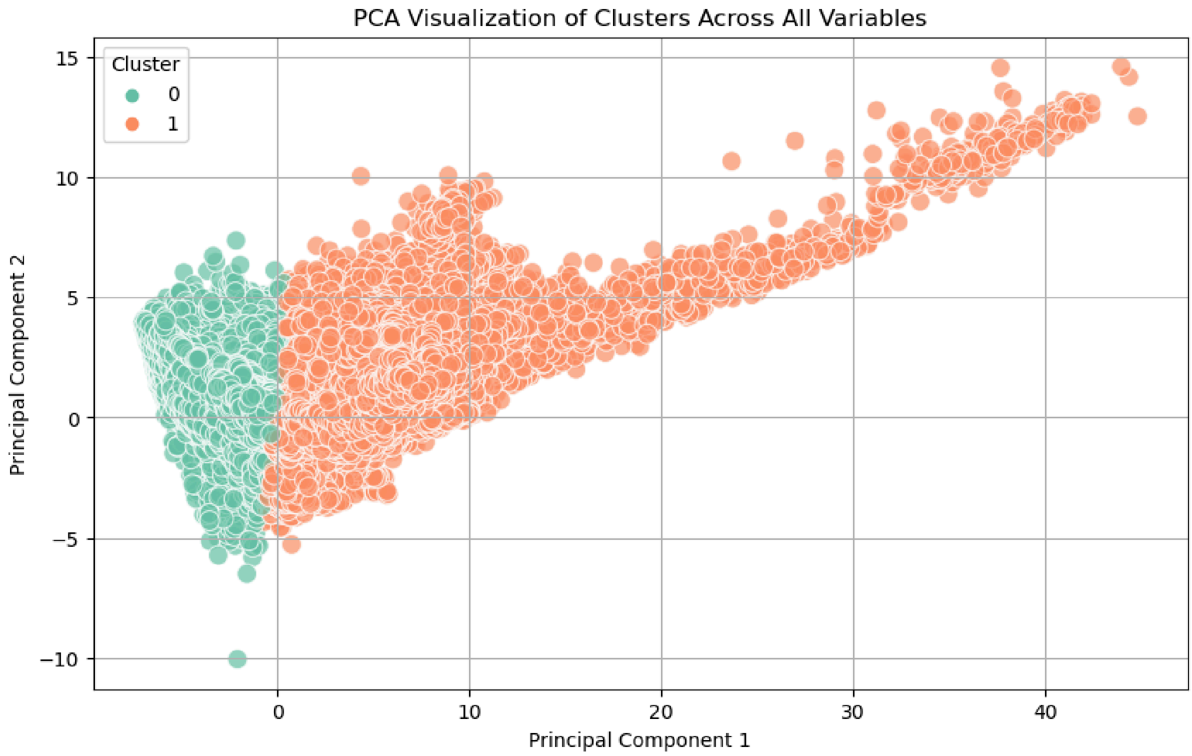
Figure(35b): line graph of clustering aggregate of all mobility variables over time Cluster 1

Clustering here refers to the grouping of countries based on all mobility variables combined. When examining the accompanying world map, it becomes evident that countries within Cluster 0 (dark blue) are primarily concentrated in Africa and parts of Asia, reflecting a robust increase in mobility activities, particularly in sectors such as workplaces and retail. The countries in this cluster may have implemented less stringent lockdowns and quickly adapted to new health guidelines, allowing for more sustained mobility.

In contrast, the regions represented by Cluster 1 (light blue) predominantly include parts of Europe, South America, North America, and Oceania, which have experienced less significant increases in mobility. The map highlights that these countries may still be grappling with the aftermath of the pandemic, where mobility remains constrained due to ongoing public health challenges and slower recovery from economic disruptions. It highlighted when there were new waves, countries in Cluster 2 struggled to maintain mobility levels.

Initially, both clusters experienced a steep decline in mobility following the announcement of the pandemic, with Cluster 1 showing a more profound impact, plummeting to nearly -60%. This trend continues into the recovery phase, where Cluster 1 struggles to return to baseline levels, not achieving this until May 2022. In contrast, Cluster 0 saw a return to baseline mobility levels as early as June 2021. By 2022, Cluster 0 experienced significant increases in all mobility variables, with grocery and pharmacy mobility peaking at over +80% above baseline levels. Meanwhile, Cluster 1's highest mobility increase was observed in parks, which, despite a sharp decline, only reached just above +40%. One commonality between the two clusters is that workplace mobility remains the lowest across both groups, highlighting the ongoing challenges in returning to pre-pandemic work patterns.

PCA Visualization of Clusters Across All Variables



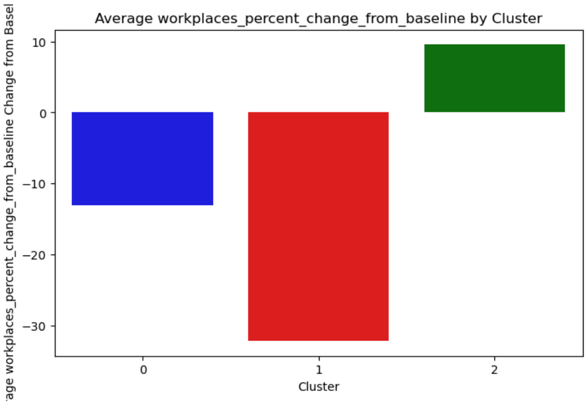
Figure(36): PCA visualisation of Cluster 1 and Cluster 2

The PCA (Principal Component Analysis) visualisation illustrates the clustering of countries based on their mobility patterns across multiple variables. The plot reveals two distinct clusters, Cluster 0 (green) and Cluster 1 (orange), which are positioned closely together, indicating that countries within these clusters exhibit similar mobility trends during the analysed periods. This proximity suggests that these countries may have experienced comparable influences, such as public health measures or economic conditions, leading to a lack of clear distinction between them. Cluster 1 (orange) shows a wider spread, reflecting greater diversity in mobility patterns among its members. This dispersion implies that the countries in this cluster experienced varying degrees of mobility changes, potentially due to differing national policies or geographic factors.

Clustering by mobility variables

The clustering analysis was conducted using each mobility variable individually rather than aggregated - alongside the five key time periods. For all the graphs, the optimal number k was determined to be 3, and each cluster was colour-coded respectively throughout cluster 0 - dark blue, cluster 1 - red and cluster 2 - green.

Clustering Workplace percentage change.



Figure(37): Bar plot of average cluster mobility for workplaces_percent_change_from_baseline by Cluster.

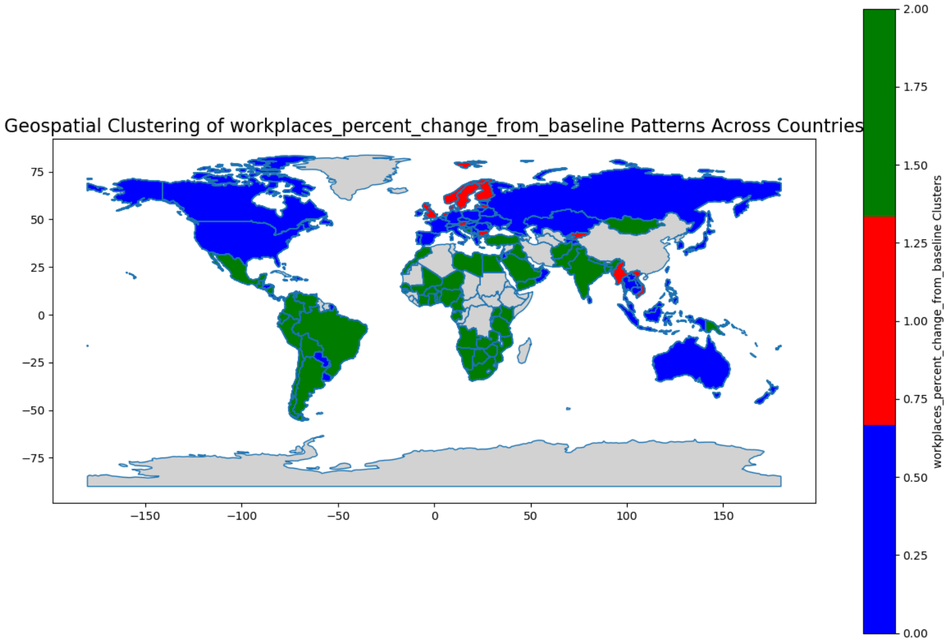
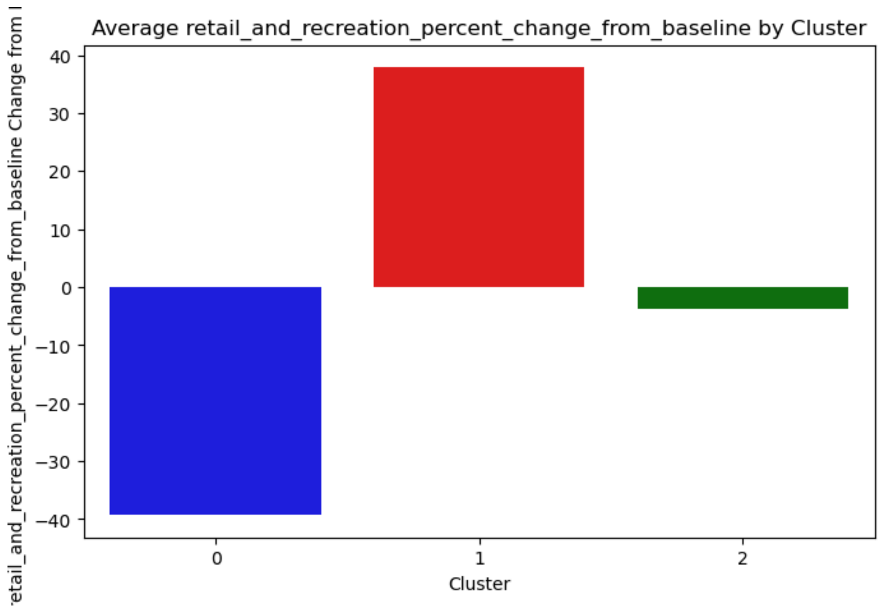


Figure (38): Geospatial Clustering of workplaces_percent_change_from_baseline Patterns Across Countries.

Cluster 0 (Dark Blue) demonstrates a notable concentration of countries experiencing significant reductions in workplace mobility, averaging around -15%. In contrast, Cluster 1 (Red) displays a moderate distribution of mobility changes, with values ranging from 0 to -35%, reflecting a broader mix of impacts. Meanwhile, Cluster 2 (Green) encompasses a smaller number of countries that exhibit positive changes in workplace mobility, primarily at lower percentages. The accompanying geospatial map visually reinforces these trends, illustrating the clustering of countries based on their responses to workplace mobility. Countries in Cluster 0 are predominantly located in North America and parts of Europe, while Cluster 1 features a more global distribution, including the United Kingdom and several nations in Scandinavia. Conversely, Cluster 2 reveals fewer instances of increased workplace mobility, particularly concentrated in regions such as Africa, South America, and South Asia.

Clustering for retail and recreating



Figure(39): Bar plot of average cluster mobility for retail_and_recreation_percent_change_from_baseline by Cluster.

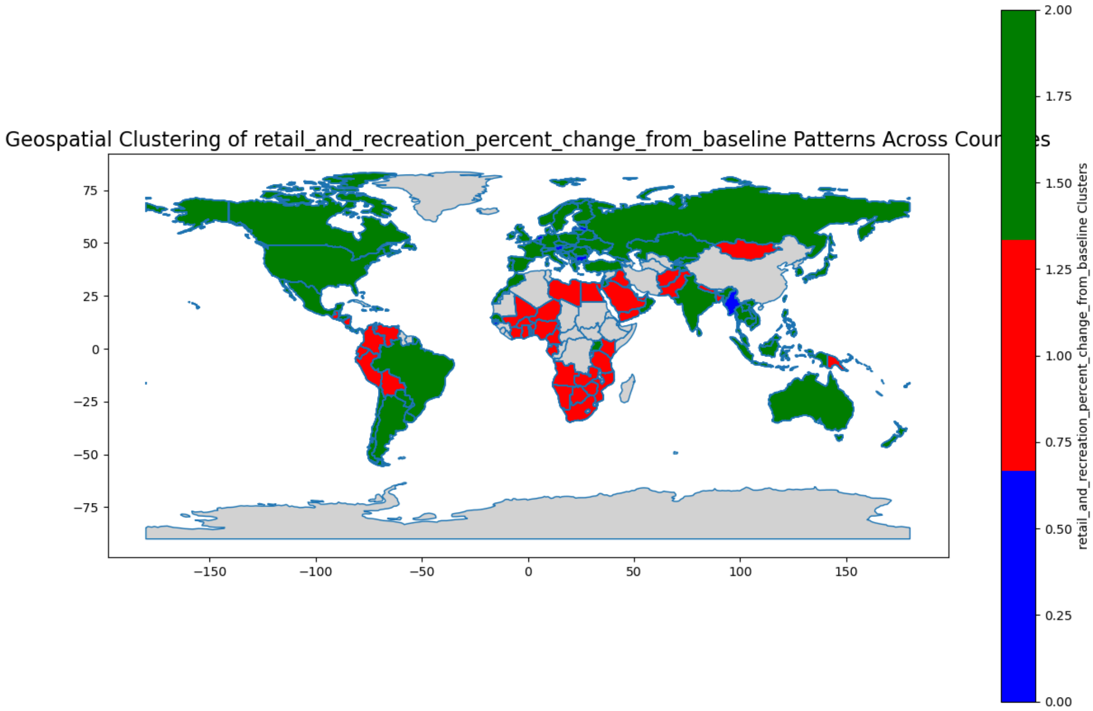
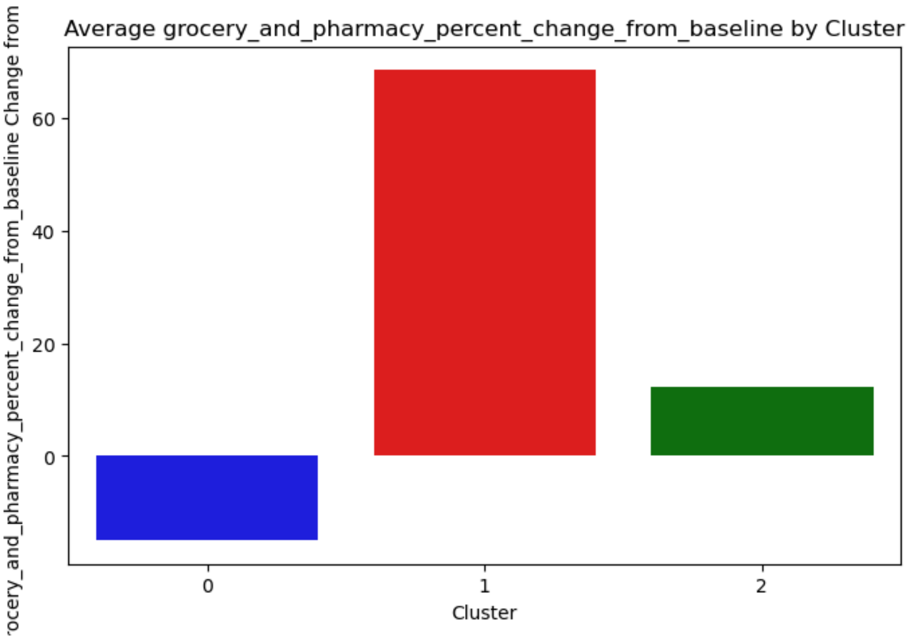


Figure (40): Geospatial Clustering of retail_and_recreation_percent_change_from_baseline Patterns Across Countries.

Cluster 0 (dark blue) encompasses a moderate number of countries exhibiting changes primarily between 0% and -40%. In contrast, Cluster 1 (Red) comprises fewer countries, with mobility changes predominantly clustered around zero and positive 40%. Notably, Cluster 2 (Green) stands out, primarily around 0%. The accompanying geospatial map effectively visualises these trends, highlighting countries in Cluster 0 scattered across Europe, indicating significant reductions in retail and recreation mobility. In contrast, Cluster 1 shows a sparse distribution, including most of Africa and notable countries like Mongolia and Afghanistan. This stands in stark contrast to Cluster 2, which demonstrates a concentrated presence, particularly in regions such as North America and parts of South America.

Clustering for grocery and pharmacy



Figure(41): Bar plot of average cluster mobility for grocery_and_pharmacy_percent_change_from_baseline by Cluster.

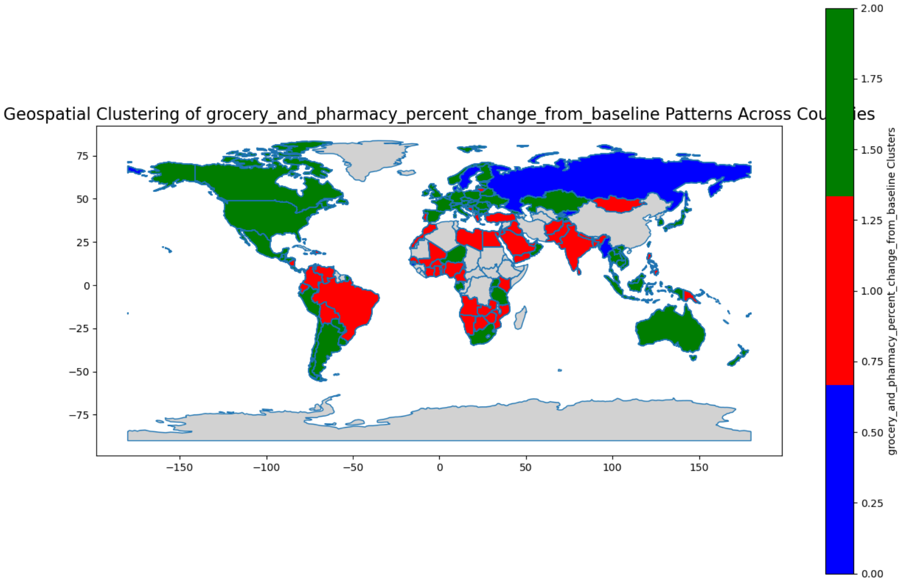
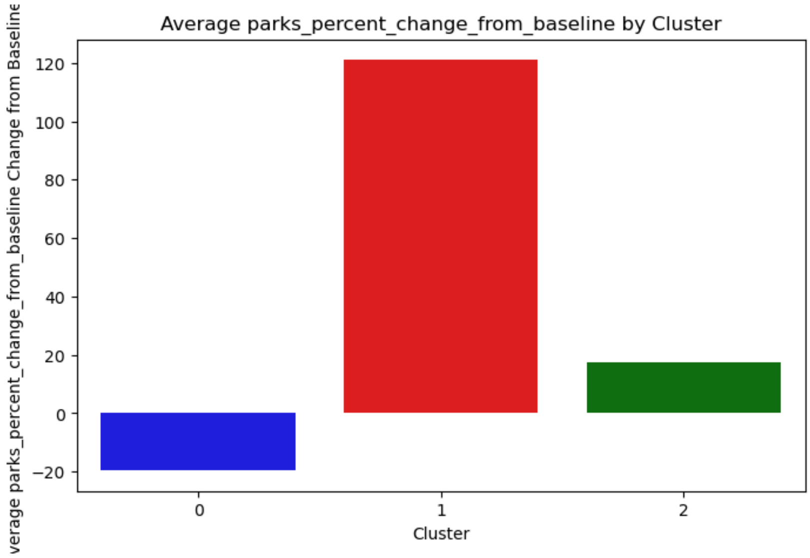


Figure (42): Geospatial Clustering of grocery_and_pharmacy_percent_change_from_baseline Patterns Across Countries.

Cluster 0 (dark blue) contains a substantial number of countries with changes ranging from 0% to -10%, indicating that many regions experienced decreases in grocery and pharmacy activity. Cluster 1 (red) captures a smaller group of countries with minimal changes but with higher increases beyond +40%. In comparison, Cluster 2 (green) shows a pronounced peak of 0 to 20%, reflecting significant positive changes for some countries.

Dark blue shades in regions such as Russia are in Cluster 0, while green areas represent more stable conditions in Cluster 2, particularly in North America. Finally, cluster 1 is most of Africa, South Asia, and South America.

Cluster for parks



Figure(43): Bar plot of average cluster mobility for parks_percent_change_from_baseline by Cluster.

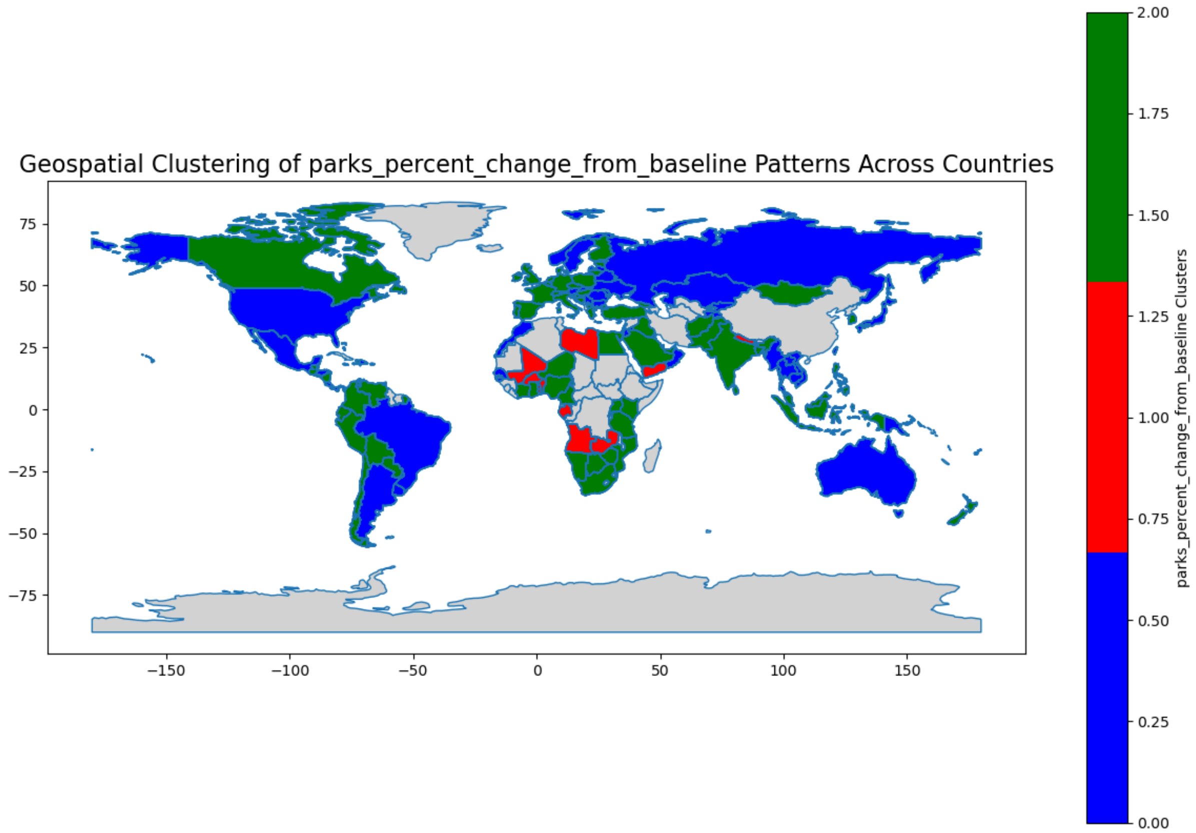
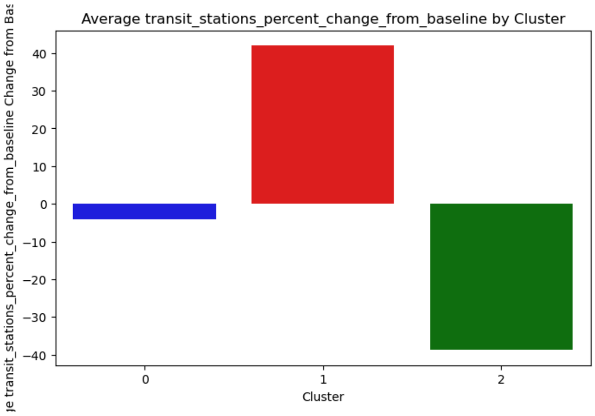


Figure (44): Geospatial Clustering of parks_percent_change_from_baseline Patterns Across Countries

Cluster 0 (dark blue) encompasses a substantial number of countries, predominantly exhibiting changes between 0% and -20%, indicating a notable decrease in park accessibility and usage. In contrast, Cluster 1 (red) consists of fewer countries but shows greater changes, with some exceeding +120%. Meanwhile, Cluster 2 (green) reflects a moderate stable increase up to +20%. This pattern underscores the strong variation in park accessibility and usage across different regions.

Cluster 0 highlights areas that have experienced significant decreases, particularly in regions such as South America, Oceania, and Asia. Conversely, many countries exhibiting Cluster 1 and Cluster 2 indicate substantial increases in park usage, further illustrating the diverse landscape of park accessibility globally.

Clustering Transit Stations



Figure(45): Bar plot of average cluster mobility for transit_stations_percent_change_from_baseline by Cluster.

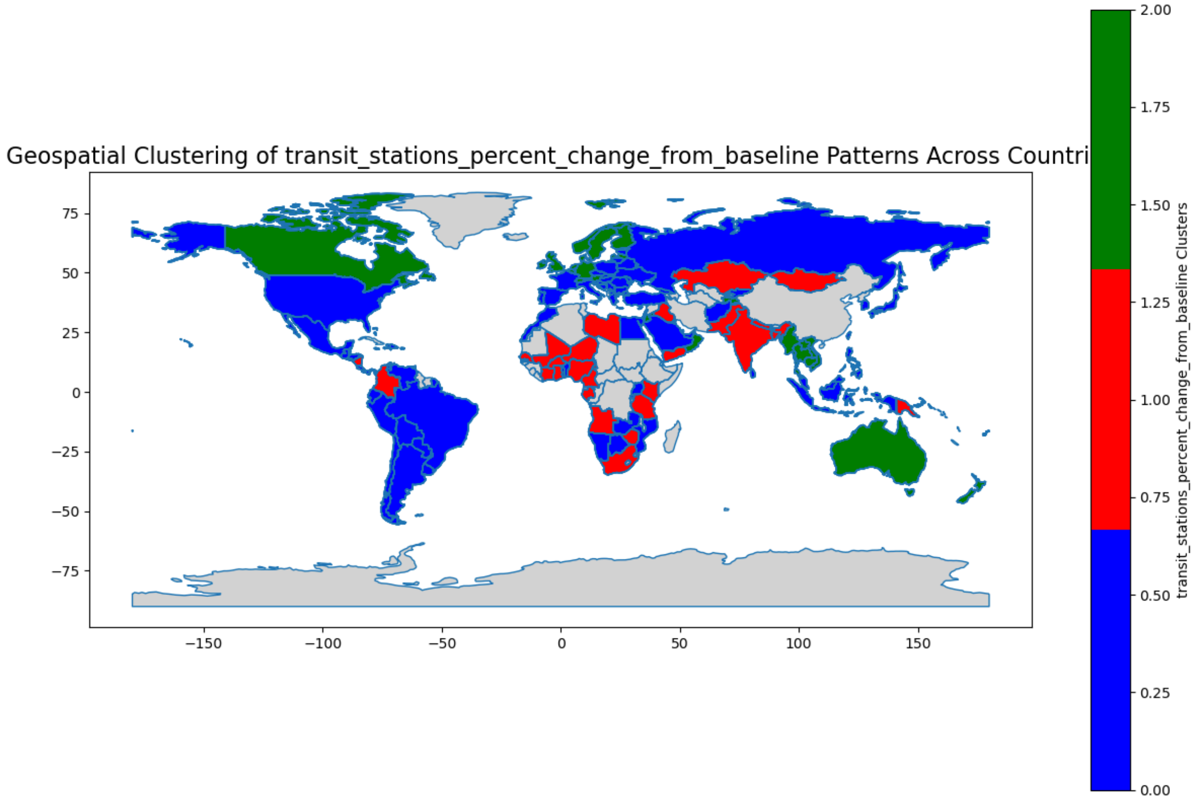
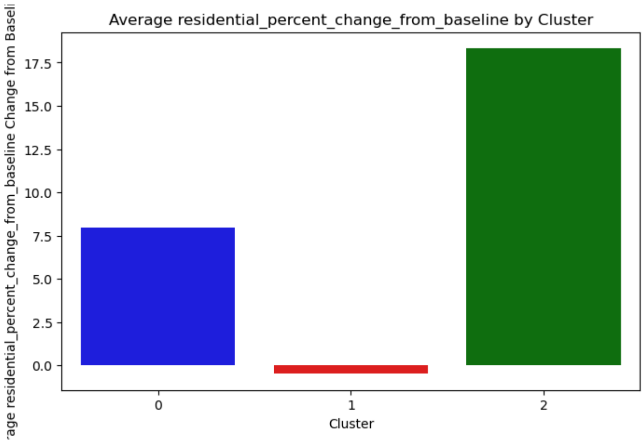


Figure (46): Geospatial Clustering of transit_stations_percent_change_from_baseline Patterns Across Countries.

Cluster 0 (dark blue) encompasses the largest number of countries, predominantly showing percentage changes around the baseline mark (0%). In contrast, Cluster 1 (red) consists of fewer countries with an average ranging up to +40%, while Cluster 2 (green) captures countries experiencing more substantial decreases in mobility.

Cluster 2 indicates significant decreases in regions, particularly in parts of Europe and South Africa., while several countries in Asia and Africa are represented in Cluster 1. Colombia, Libya, Mongolia and India are the countries that stick out in Cluster 1.

Cluster for residential



Figure(47): Bar plot of average cluster mobility for residential_percent_change_from_baseline by Cluster.

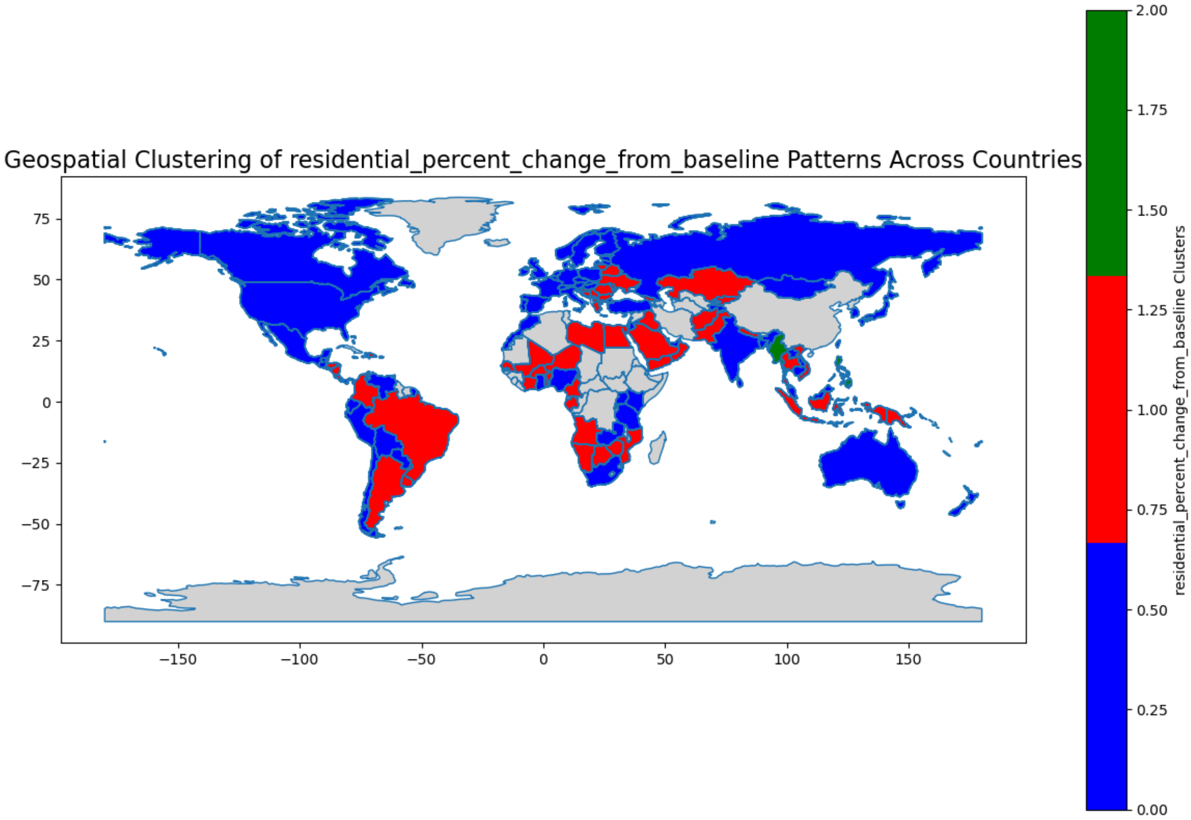


Figure (48): Geospatial Clustering of residential_percent_change_from_baseline Patterns Across Countries.

Cluster 0 (dark blue) encompasses a substantial number of countries, exhibiting changes primarily between 0% and 7.5%, indicating a general increase in residential activity. In contrast, Cluster 1 (red) includes a larger share of countries with similar usage around baseline levels. Meanwhile, Cluster 2 (green) represents a smaller proportion of countries, with an average of +20%.

Cluster 0 is prominent globally, while Cluster 1 is also well represented in countries, particularly in Asia and South America. Conversely, Cluster 2 features very few countries on the choropleth map, and Myanmar is the most visible country in this cluster.

4.4 Stay-at-home restrictions

Stay-at-Home Requirements

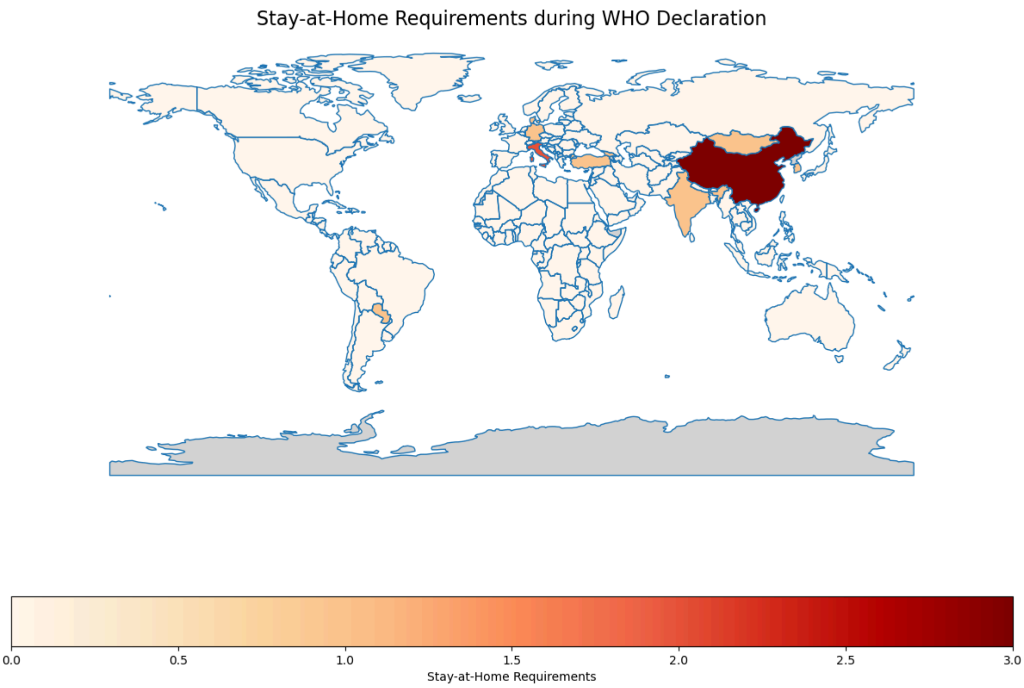


Figure (49a) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

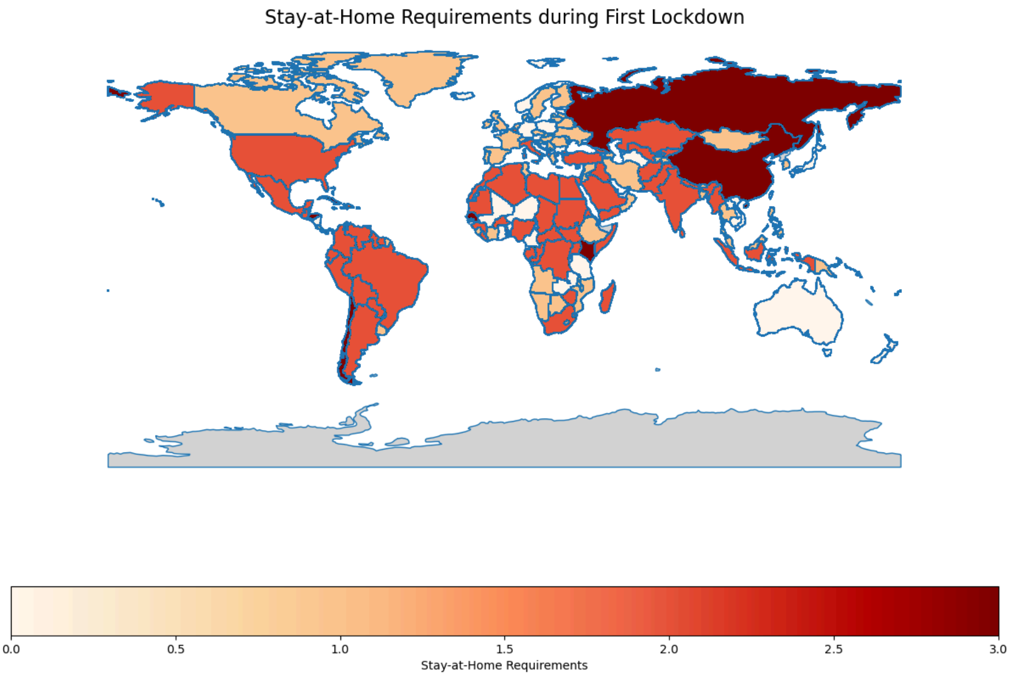


Figure (49b) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

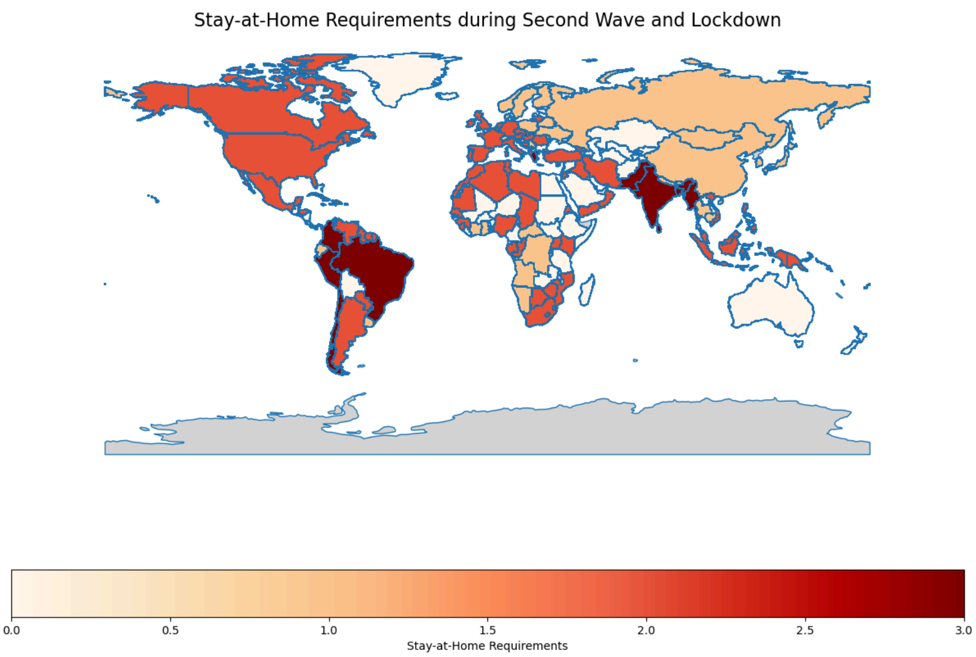


Figure (49c) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

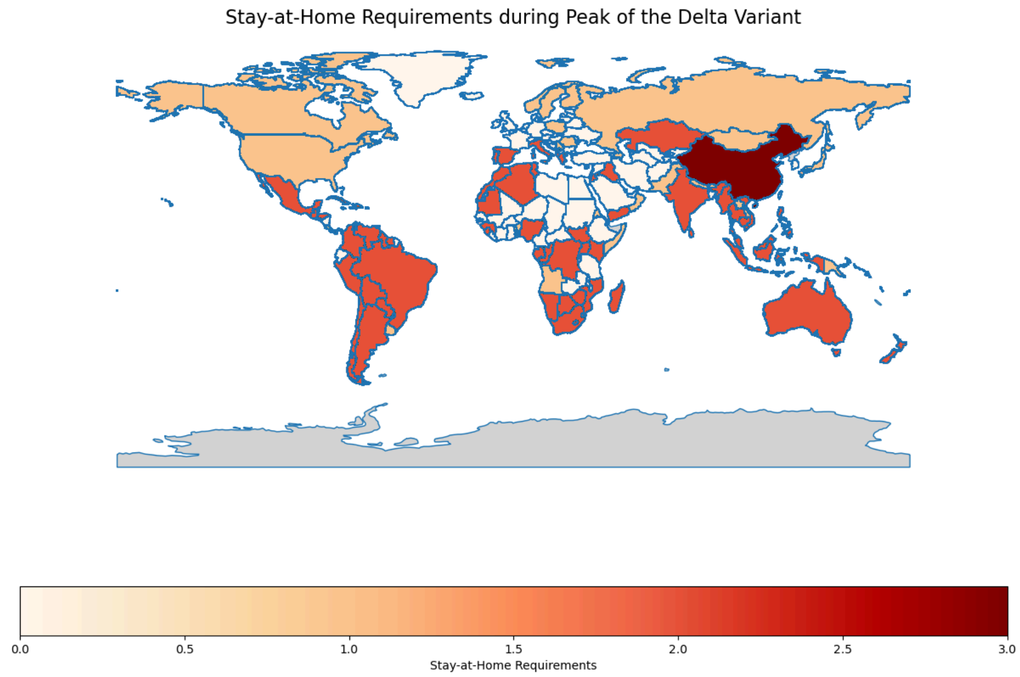


Figure (49d) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

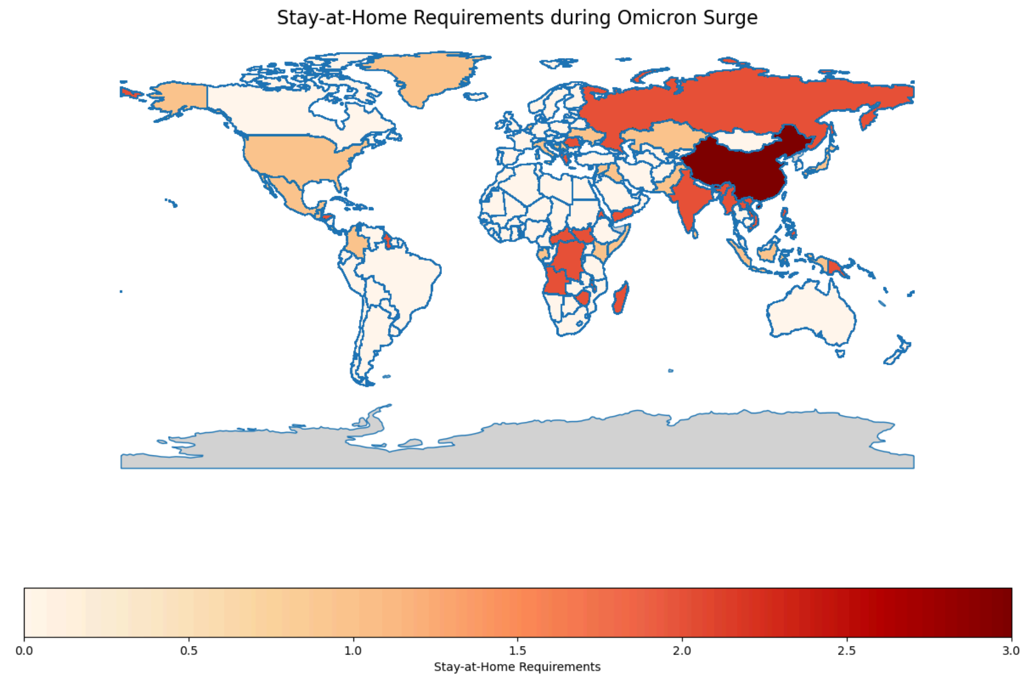


Figure (49e) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

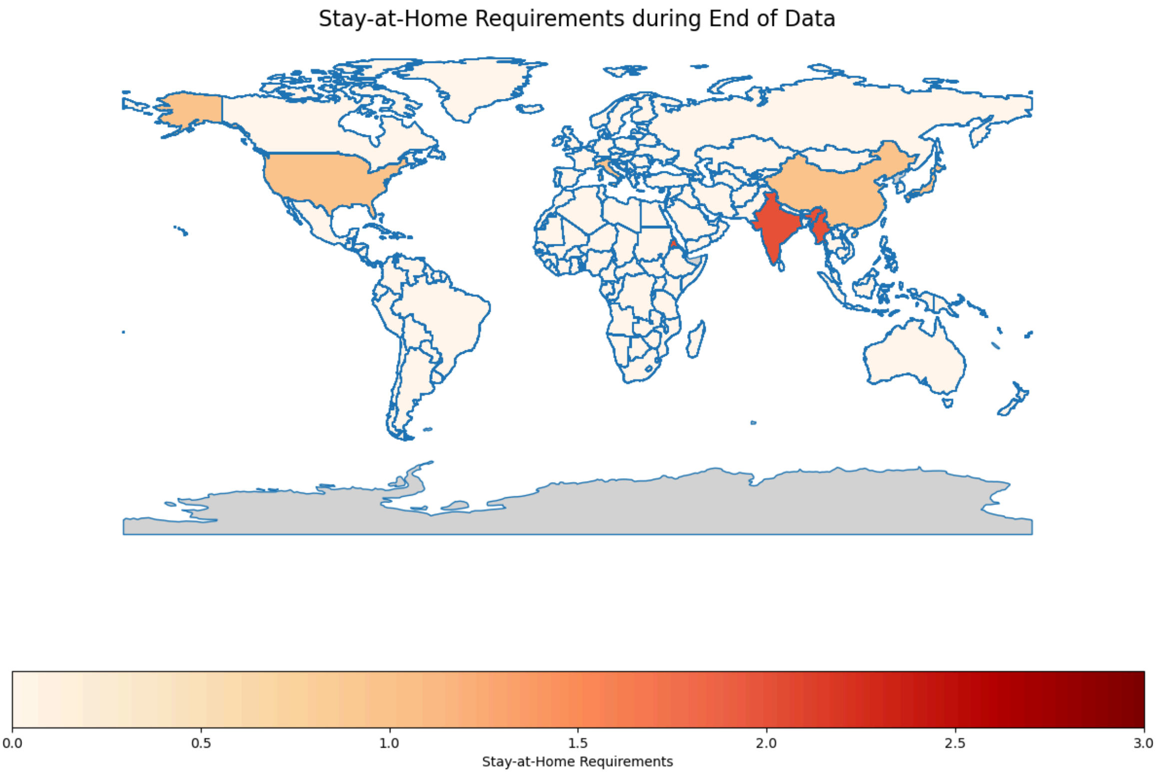


Figure (49f) Chloropoleth map of Stay-at-Home Requirements During Key COVID-19 Phases

The sequence of maps illustrates the evolution of stay-at-home requirements worldwide during critical phases of the COVID-19 pandemic, highlighting changes in government responses to varying levels of threat.

In the initial phase following the WHO's pandemic declaration Figure (49a), stay-at-home requirements were selectively implemented, with countries like China, India, and some European nations applying more stringent measures. This early response reflects the need to control initial outbreaks, particularly in countries facing high case numbers and limited healthcare resources.

During the first lockdown, stay-at-home measures became widespread, with most regions adopting stringent restrictions. This unified global response underscores the urgency to contain the virus as cases rapidly increased, leading to nationwide lockdowns across various countries. Similarly, the second wave and lockdown still had worldwide restrictive measures in place; however, more extreme measures shifted to the West, particularly in North America and South America.

The emergence of the Delta variant Figure (49d) saw a resurgence in stay-at-home orders, especially across Asia, with China adopting some of the most stringent measures globally. This phase highlighted the challenges posed by the more transmissible variant, prompting many countries to reintroduce strict lockdowns to curb the spread, particularly where vaccination coverage was still ramping up.

With the Omicron variant surge Figure (49e), global responses varied, with China continuing stringent measures, while Europe, Africa, and parts of the Americas exhibited almost no restrictions.

By the end of the data period Figure (49f), most regions had substantially relaxed restrictions, with only a few areas, such as India, China and the United States, maintaining moderate stay-at-home requirements. This final map reflects the global transition towards living with COVID-19 as an endemic virus, with countries moving away from strict lockdowns in favour of less restrictive approaches aided by vaccination efforts and improved treatment options.

Changes in Mobility Across Sectors in Relation to Stay-at-Home Requirements Over Time

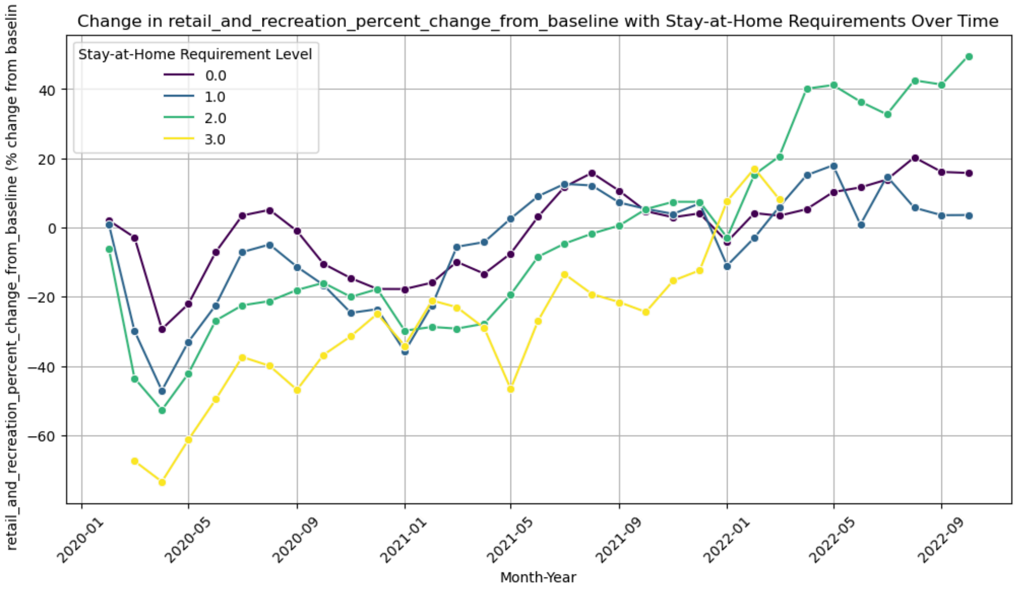


Figure (50a) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

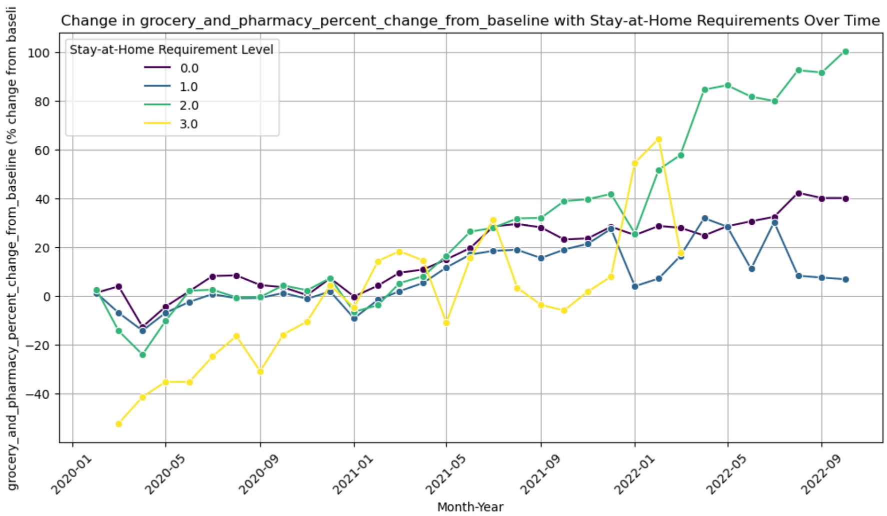


Figure (50b) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

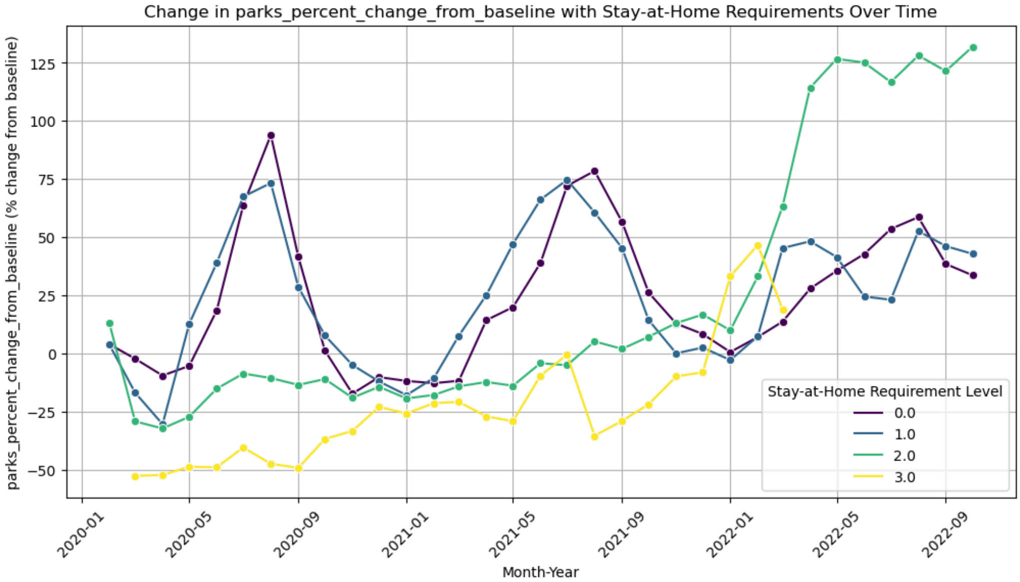


Figure (50c) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

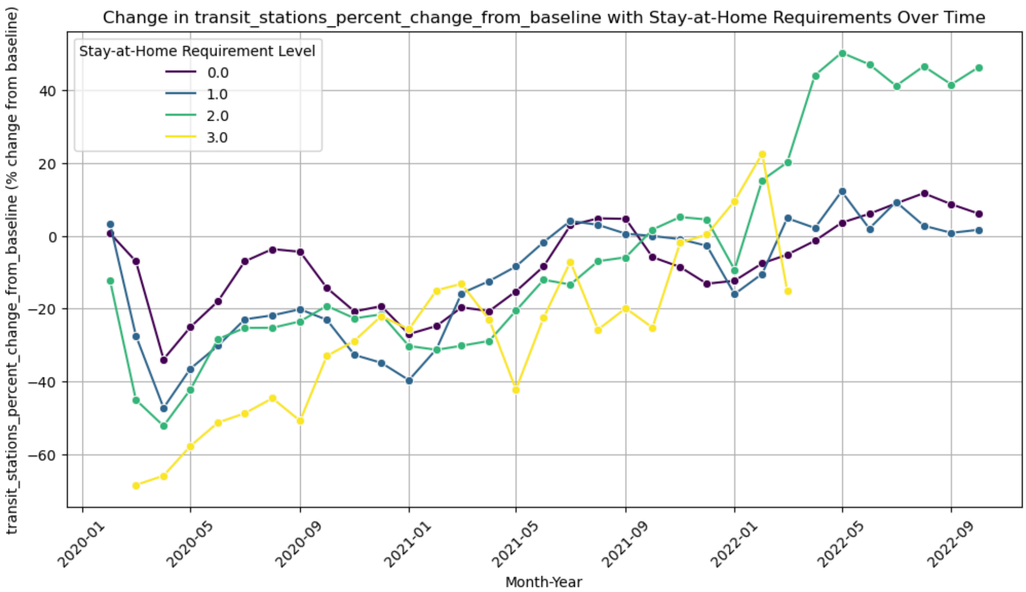


Figure (50d) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

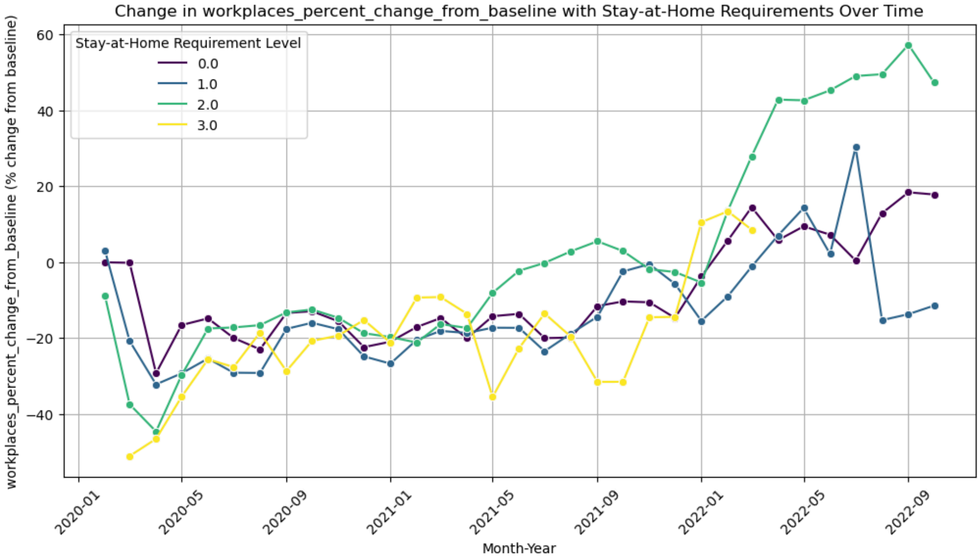


Figure (50e) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

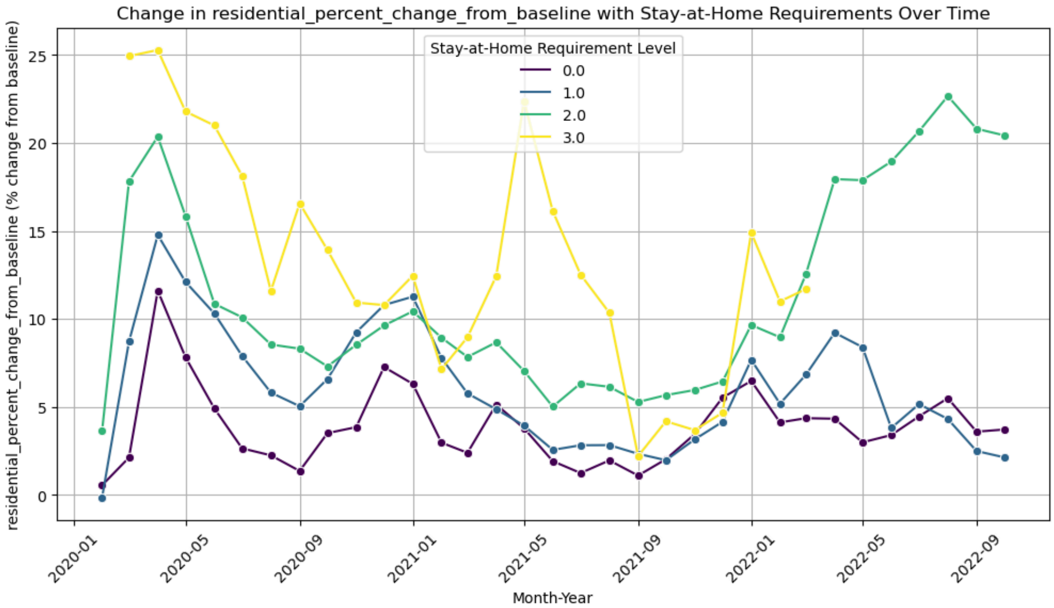
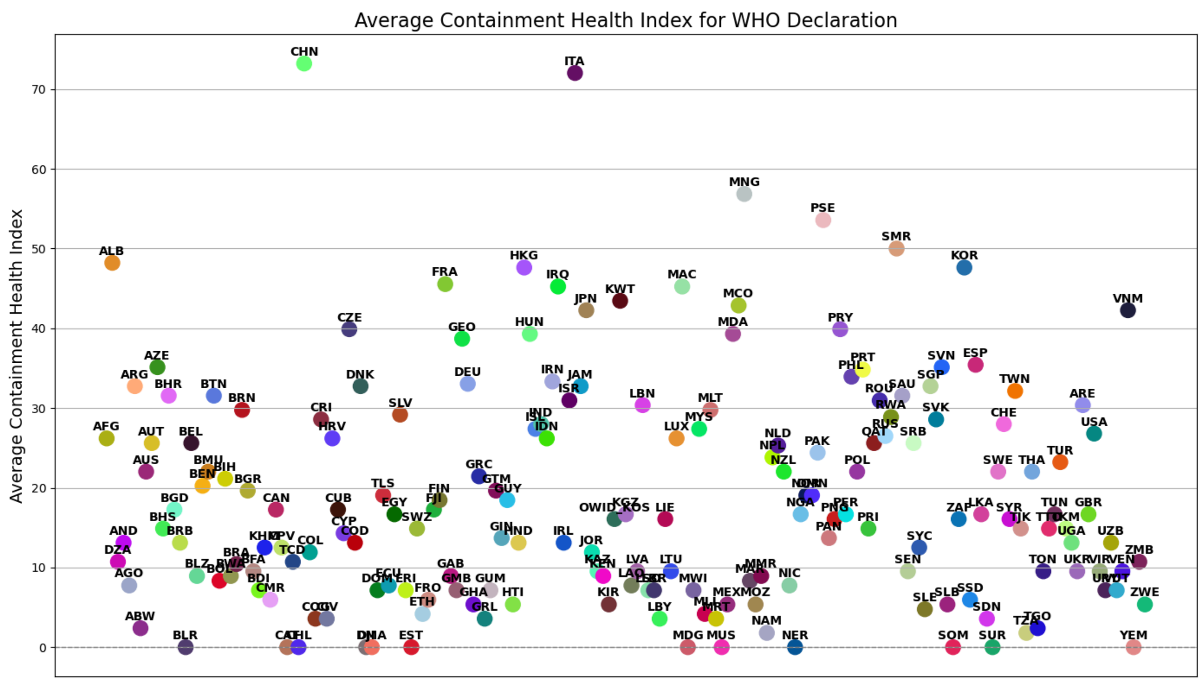


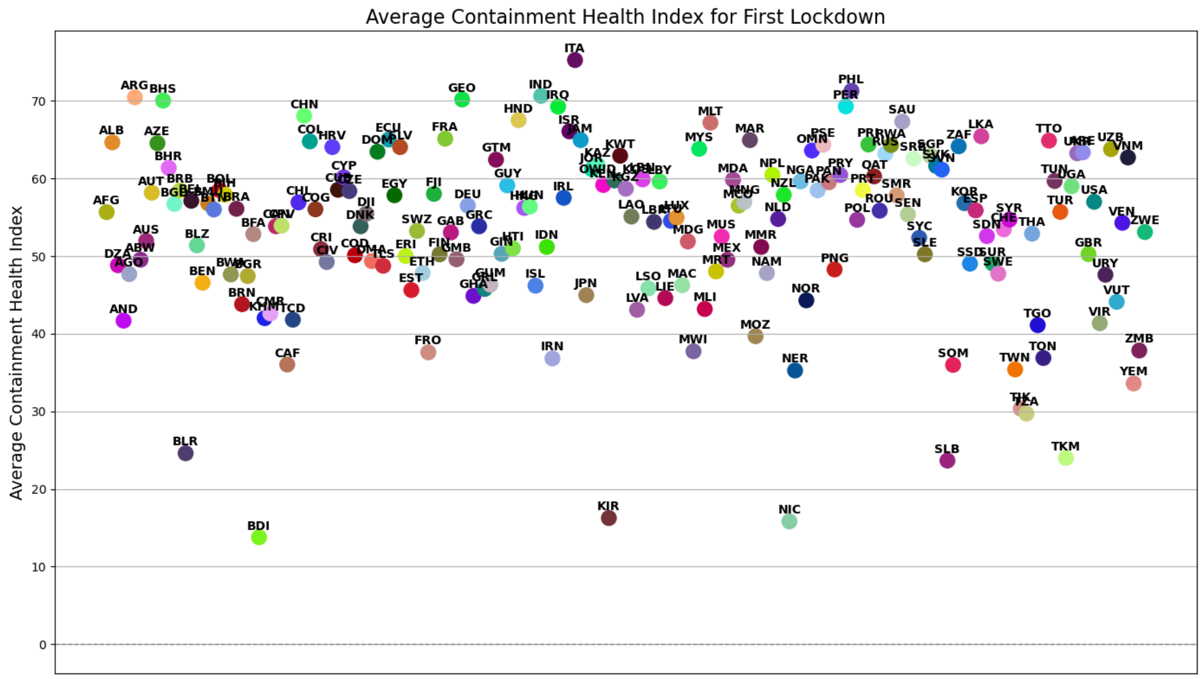
Figure (50f) - Line graph Analysis of Mobility Changes by Stay-at-Home Requirement Levels Across Sectors

The graphs illustrate the impact of stay-at-home requirements on mobility across various sectors over time, revealing consistent patterns. It is important to note that the values represented in these graphs are aggregated over groups of countries that had the same stay-at-home requirement level (from 0 to 3) at each time step (from January 2020 to September 2022). Consequently, each point on any line corresponds to a different group of countries, meaning that values from different time steps are not strictly comparable. This aggregation method reflects the varying impacts of stay-at-home requirements on mobility across different regions, and the interpretations should be made with this context in mind. Notably, the strictest stay-at-home requirement, level 3, shows a peak across most sectors in late 2021, with the exception of residential mobility, which starts at its highest level and reaches a peak in May 2021. This reflects heightened restrictions and prolonged time spent at home during these periods. Additionally, stay-at-home requirement level 2 consistently rises toward the end of each graph, suggesting that by late 2022, most regions around the world had implemented moderate restrictions at level 2, indicating a shift toward maintaining some level of mobility restriction while easing the strictest lockdowns.

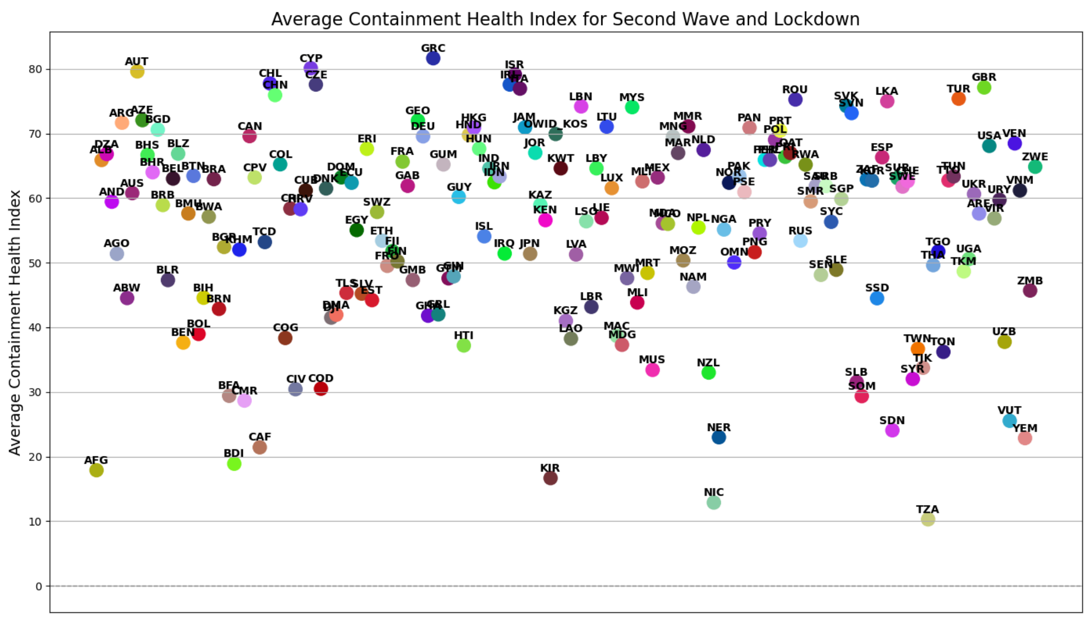
Government Containment Health Index Across Key COVID-19 Periods



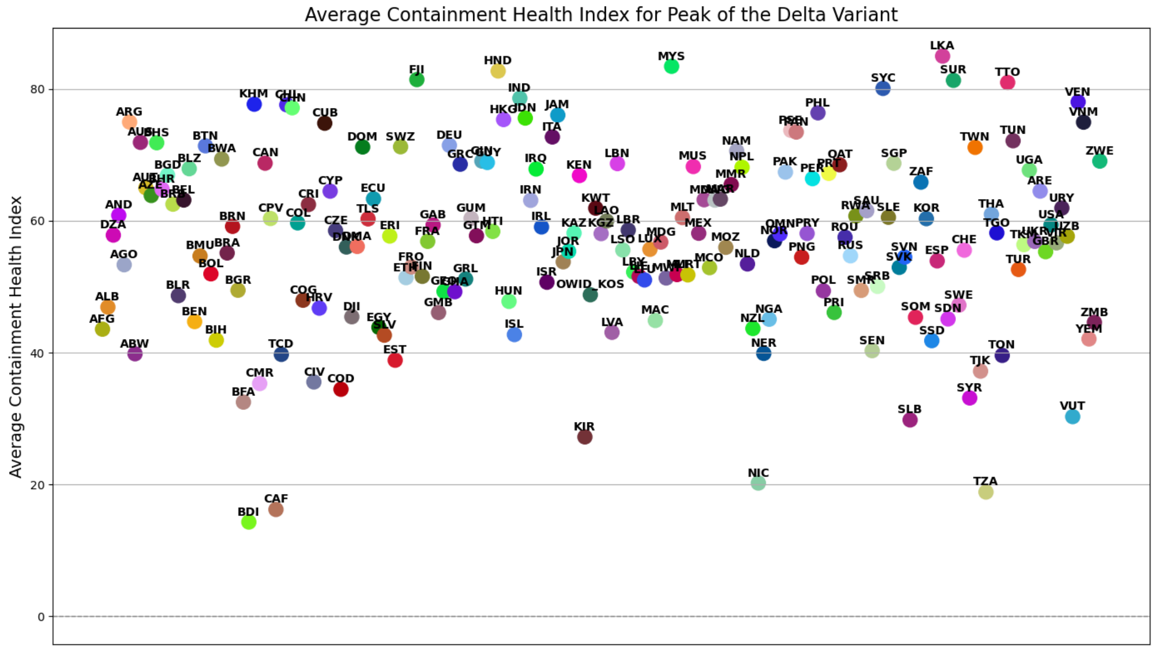
Figure(51a): Scatter plot showing containment index



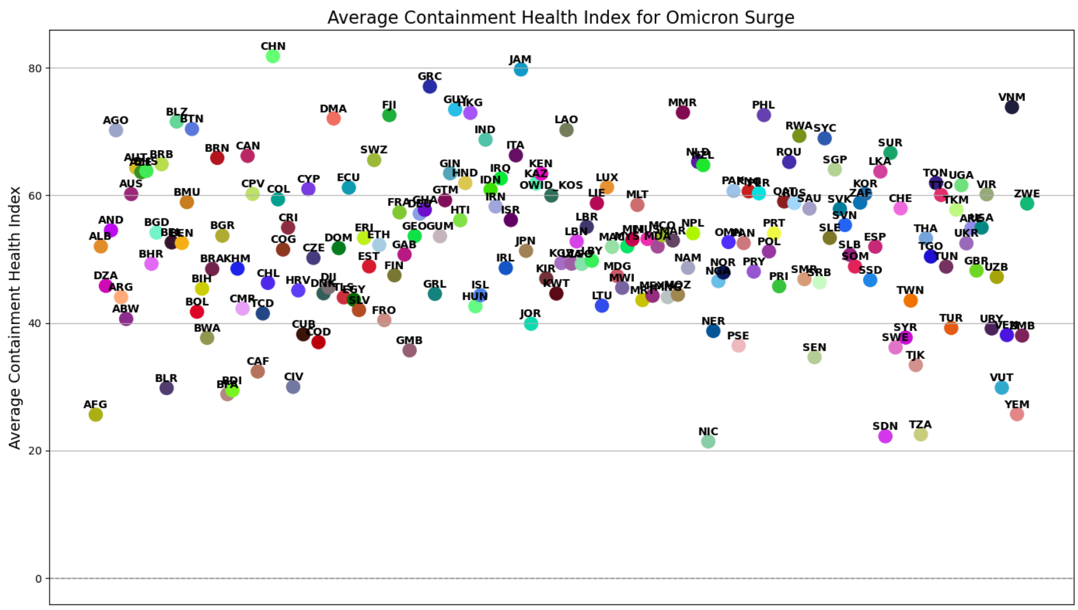
Figure(51b): Scatter plot showing containment index



Figure(51c): Scatter plot showing containment index



Figure(51d): Scatter plot showing containment index



Figure(51e): Scatter plot showing containment index

This plot looks at the government containment index implemented by countries specifically for key periods during the pandemic, illustrating how each country's average containment health index varied over time. By visualising these fluctuations, the effectiveness of different containment measures across various nations can be assessed, providing insights into how countries responded to the evolving public health crisis. The x-axis is hidden as it contains every country's abbreviation.

During the WHO Declaration period, China (CHN) and Italy (ITA) recorded the highest restriction levels, with values of 73.21 and 72.02, respectively, indicating early, strict responses. Mongolia (MNG) also showed high restrictions, with a value of 56.85. In contrast, Belarus (BLR), the Central African Republic (CAF), and Chile (CHL) showed no recorded stay-at-home measures, reflecting either a lack of restrictions or delayed implementation.

In the First Lockdown period, Italy (ITA) remained one of the strictest, with a high level of 75.27, joined by the Philippines (PHL) at 71.30 and India (IND) at 70.66, demonstrating rigorous lockdowns as countries attempted to curb the virus's spread. On the other hand, Burundi (BDI), Nicaragua (NIC), and Kiribati (KIR) recorded low restriction levels, suggesting a minimal or delayed lockdown approach.

During the Second Wave and Lockdown, Greece (GRC), Cyprus (CYP), and Austria (AUT) exhibited the highest restriction levels, with Greece reaching 81.65. This period saw certain European countries reinforcing strict measures to combat resurgent cases. Meanwhile, Tanzania (TZA), Nicaragua (NIC), and Kiribati (KIR) again showed very low levels of restrictions, indicating a continued less restrictive approach in these regions.

In the Peak of the Delta Variant, Sri Lanka (LKA), Malaysia (MYS), and Honduras (HND) reached the highest restriction levels, with Sri Lanka at 85.00, reflecting strict measures in response to the highly transmissible Delta variant. At the same time, countries like Burundi (BDI), the Central African Republic (CAF), and Tanzania (TZA) remained among those with the lowest restriction levels, highlighting regional disparities in response intensity.

Finally, during the Omicron Surge, China (CHN) again recorded high restrictions at 81.82, reflecting its commitment to a zero-COVID strategy. Jamaica (JAM) and Greece (GRC) also imposed strict measures with values of 79.74 and 77.06, respectively. In contrast, Nicaragua (NIC), Sudan (SDN), and Tanzania (TZA) had lower restrictions, indicating either a shift to more lenient policies or less concern regarding the Omicron variant's impacts.

Overall, the data shows that countries like China, Italy, and Greece consistently imposed some of the highest restriction levels across different COVID-19 waves, while countries such as Nicaragua, Tanzania, and Burundi often had the lowest,

4.5 Hierarchiel Clustering

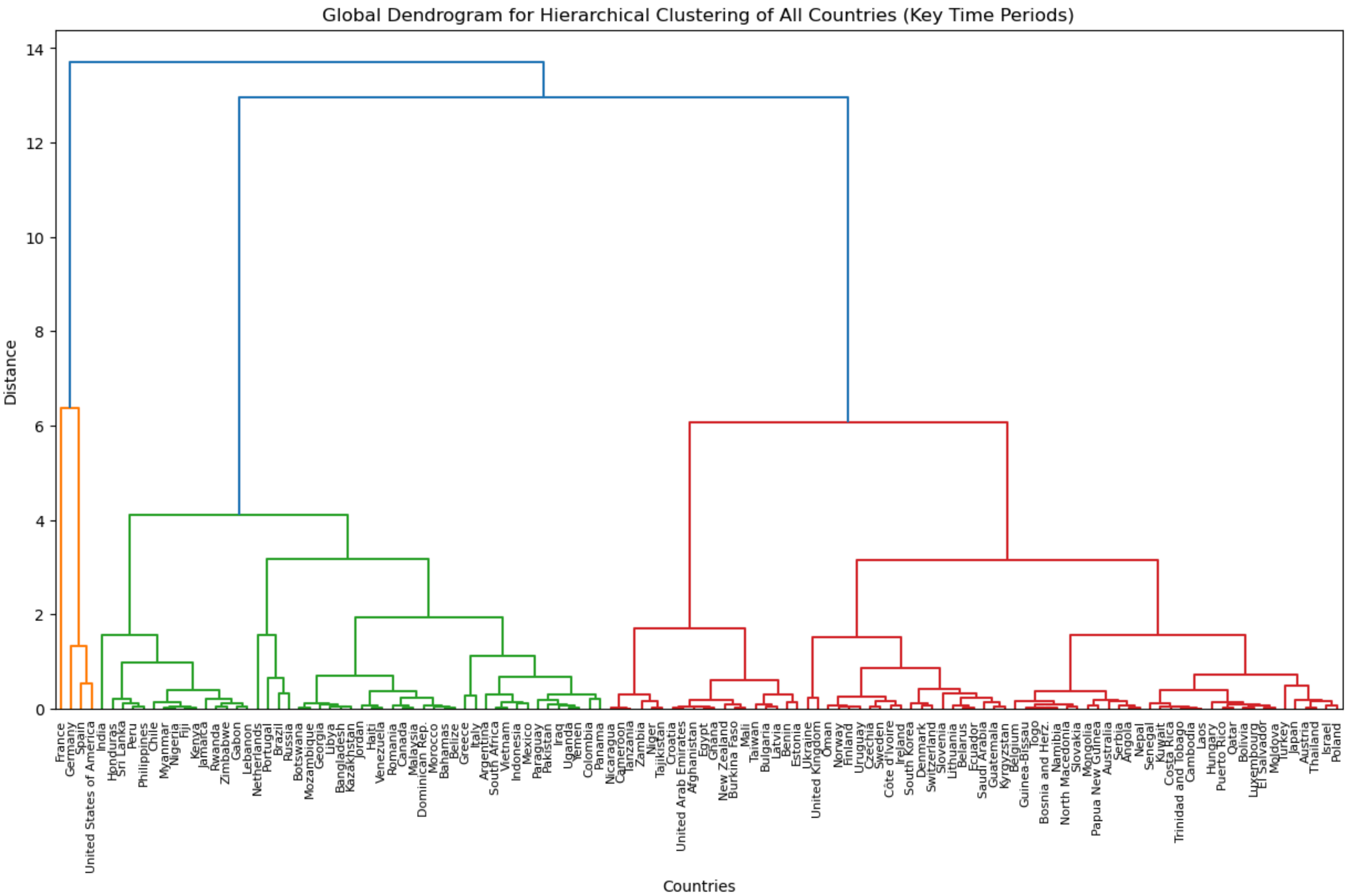
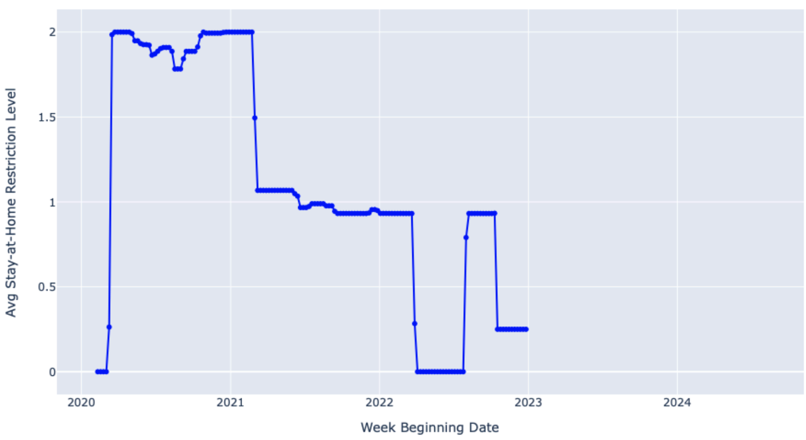
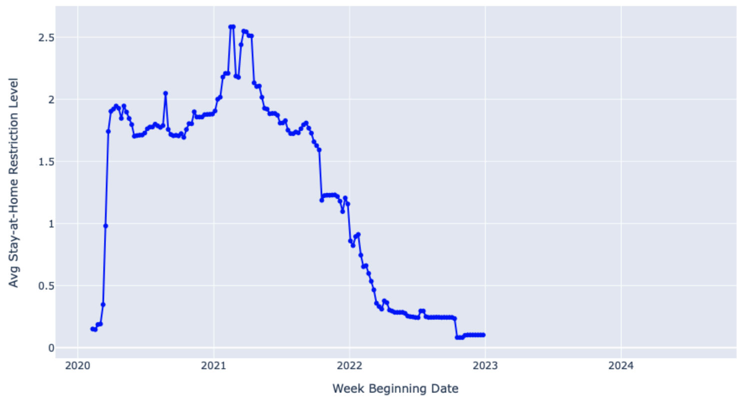


Figure (52): Dendrogram of hierachiel clustering

Weekly Avg Stay-at-Home Restrictions for Cluster 1



Weekly Avg Stay-at-Home Restrictions for Cluster 2



Weekly Avg Stay-at-Home Restrictions for Cluster 3

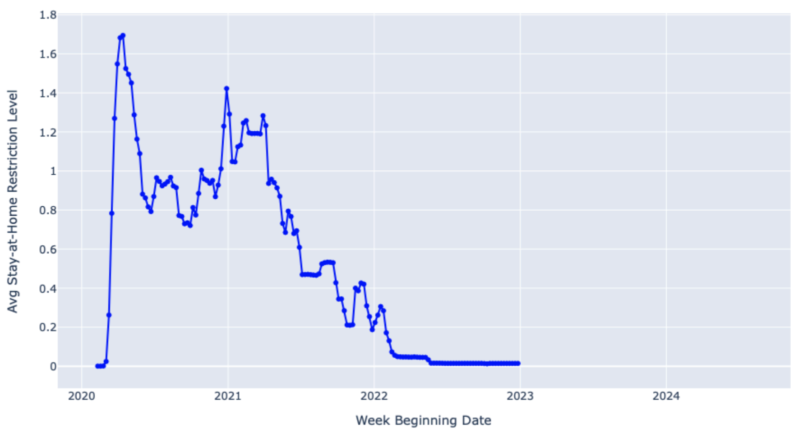


Figure (53): Stay-at-Home Restriction Trends for Country Clusters

The dendrogram clusters reveal distinct patterns in stay-at-home restrictions among countries. The chosen number of clusters was 3 clusters based on the cutting level of 10. Cluster 1 consists of countries such as the United States of America and France, which maintained moderately high restrictions (severity level 2) throughout most of the pandemic until early 2021 when the severity gradually dropped to level 1 and continued to ease through 2022. These nations implemented moderate, sustained restrictions before slowly relaxing them. Cluster 2 includes countries like Italy, Bangladesh, Yemen, and Libya, which initially imposed restrictions at level 2, peaking in mid-2021 at an average severity of 2.5. These countries then sharply reduced restrictions shortly afterwards, reflecting a period of strict, extended lockdowns followed by a rapid easing of measures. Cluster 3 is characterised by an early peak in restrictions at an average level of 1.7, followed by a steady reduction to level 0. This cluster includes countries such as the United Kingdom and Mali, which enforced strong early restrictions but transitioned more quickly to minimal measures as the pandemic evolved, adapting to a new normal sooner than the other clusters.

Weekly Mobility Variables and Predicted Trends for Clusters 1, 2, and 3

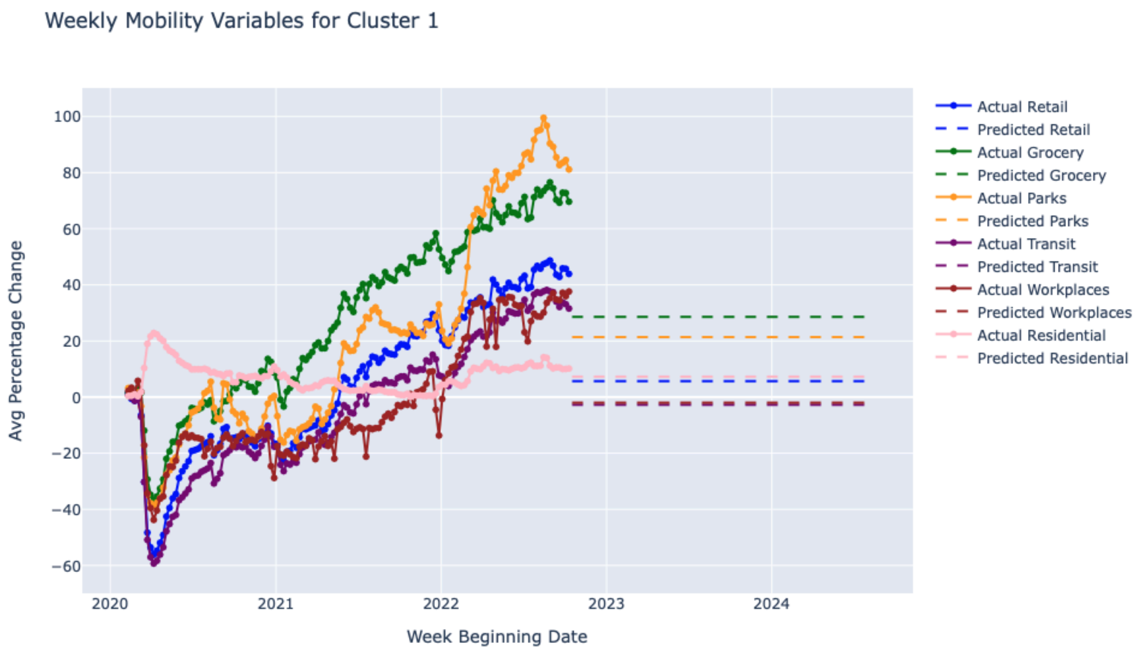


Figure (54a): Weekly Mobility Variables with Predicted Trends for Clusters 1

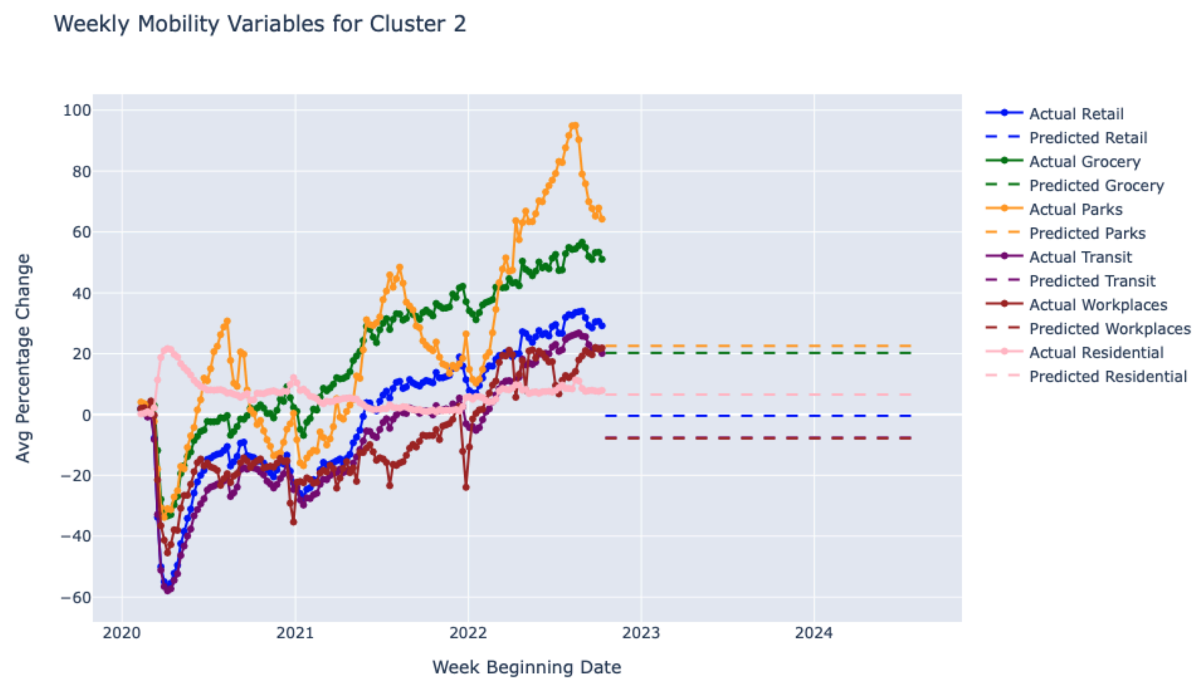


Figure (54b): Weekly Mobility Variables with Predicted Trends for Clusters 2

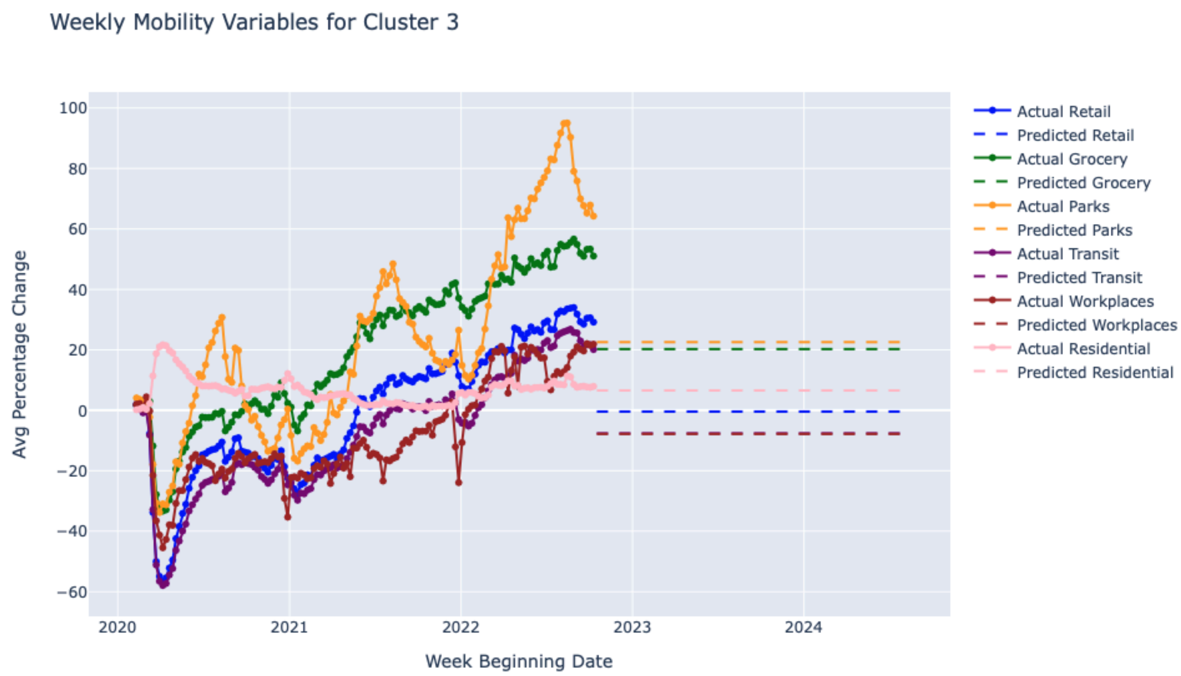


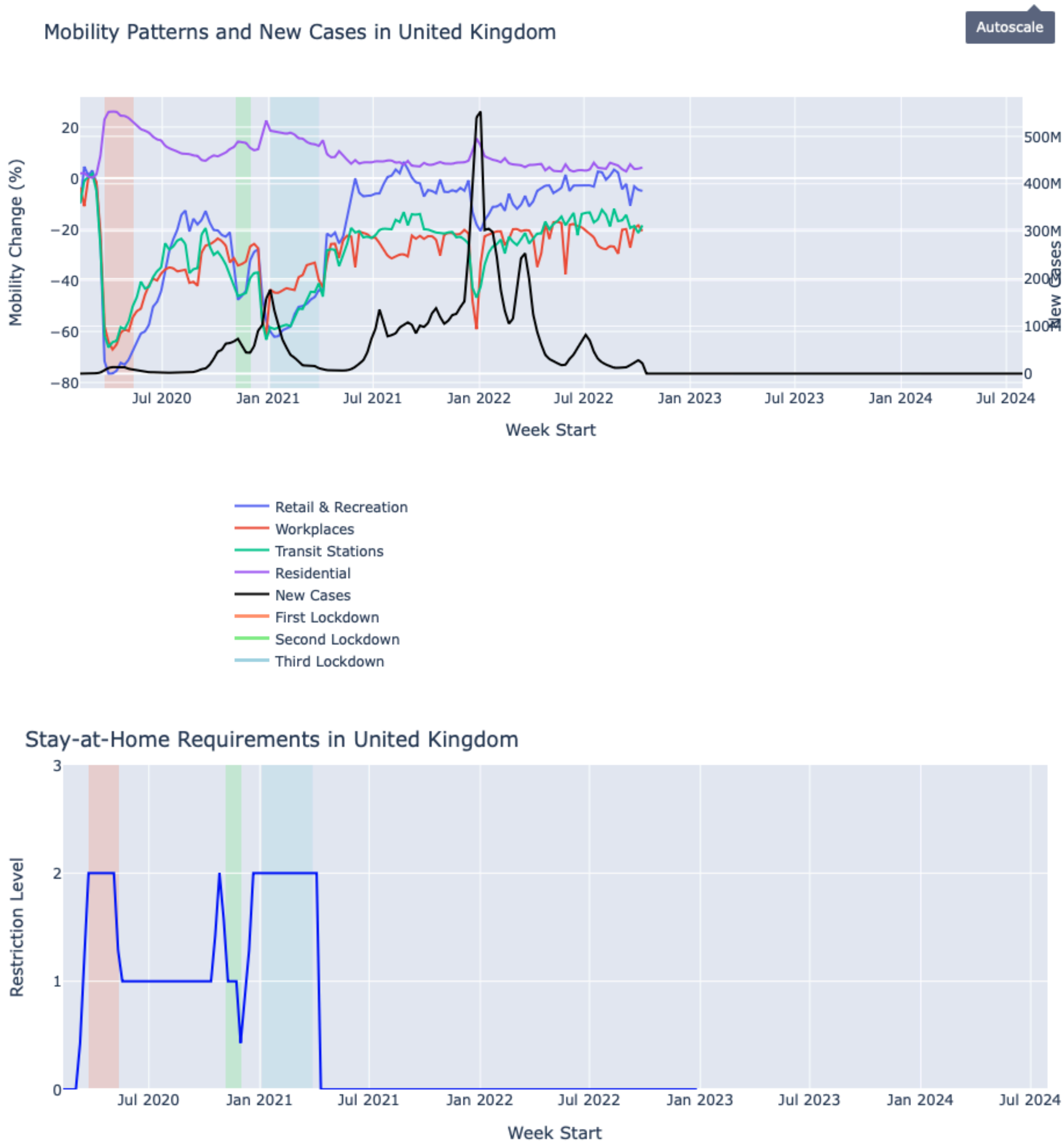
Figure (54c): Weekly Mobility Variables with Predicted Trends for Clusters 3

The three clusters show similar mobility trends with varying degrees, with park mobility being the highest and residential mobility the lowest at the end of the observed data. Looking at the predicted values for July 2024, mobility levels for each variable within each cluster are expected to decrease compared to current levels.

In Cluster 1, the predicted values indicate that mobility across all categories will decline slightly towards baseline levels. Grocery mobility, currently at +69.63%, is expected to drop to +28.58%, remaining the highest among variables. Transit is projected to have the lowest mobility, decreasing from +22.96% to -7.61%, likely reflecting reduced reliance on public transportation as other sectors stabilise or decline. Clusters 2 and 3 show similar patterns, with park mobility expected to remain the highest, although with significant decreases. For example, in Cluster 2, park mobility is predicted to drop from +64.23% to +22.54%. The lowest mobility variable in both clusters is predicted to be workplaces, which will fall below baseline levels; in Cluster 2, workplace mobility is expected to decline from +21.86% to -7.81%. These predicted declines suggest a general reversion toward pre-pandemic mobility patterns across all clusters, with public spaces like parks remaining more active but workplace and transit mobility potentially seeing reduced demand as new working patterns become established.

In summary, while Clusters 2 and 3 share similar mobility trends across the different variables, Cluster 1 distinctly diverges with pronounced declines in mobility for grocery, transit, and workplace categories.

4.6 Individual Country-level Analysis



Figure(55a): Double line graph showing mobility variables change over time, new cases and stay-at-home requirement - United Kingdom

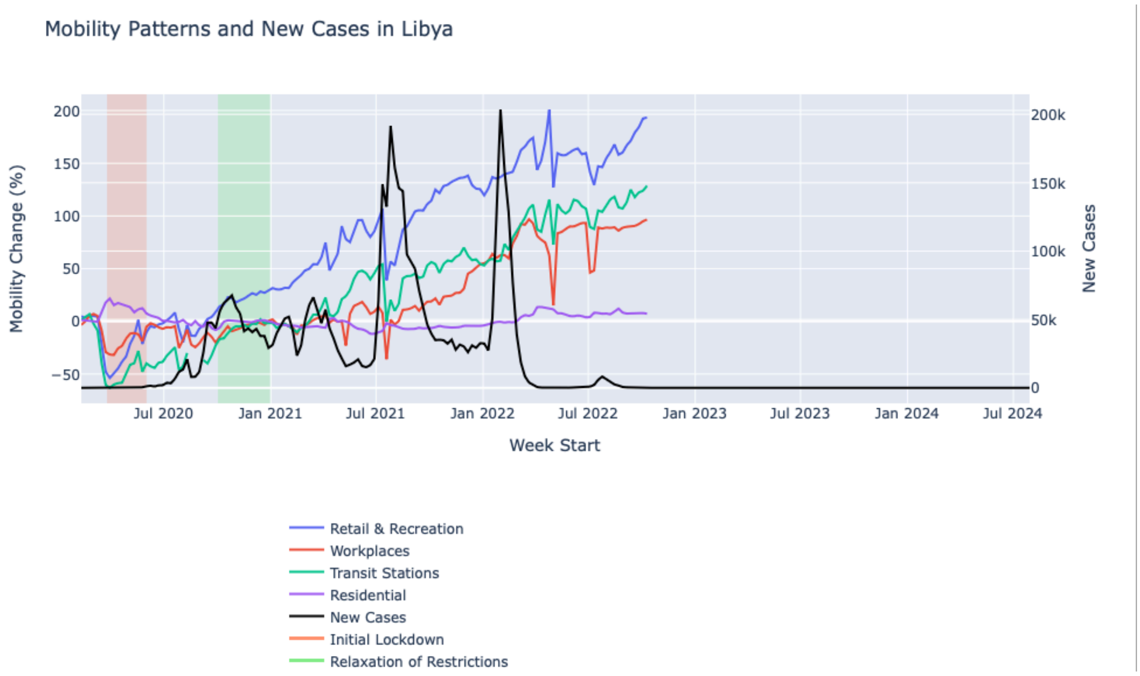
The restriction levels indicate that the UK implemented level 2 stay-at-home requirements during the early months of 2020, with a temporary relaxation in mid-2020, before reintroducing level 2 restrictions in January 2021. By mid-2022, restrictions were reduced to zero, signalling the easing of stay-at-home requirements.

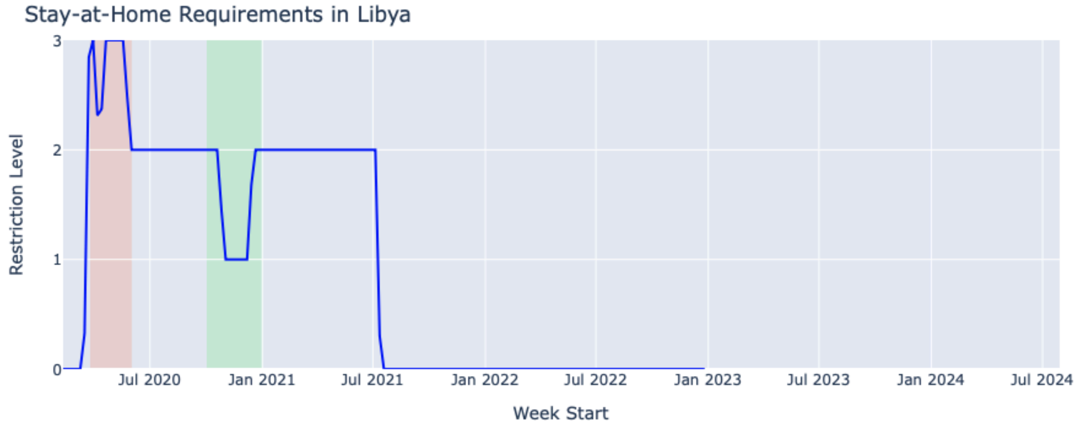
The mobility graph shows a significant spike in COVID-19 cases in January 2021, which coincided with an increase in restriction levels, marking the onset of the UK's third lockdown (shaded in blue). Interestingly, there was another surge in cases in January 2022; however, this time, no stay-at-home restrictions were implemented, reflecting a shift in the UK's pandemic response strategy, likely influenced by vaccination coverage and the adaptation to living with the virus.

Figure(55b): Double line graph showing mobility variables change over time, new cases and stay-at-home requirement - Sweden

The stay-at-home restrictions and mobility data for Sweden reveal a unique response strategy compared to many other countries. In the first graph, Sweden maintained relatively low restriction levels throughout the pandemic, reaching a maximum restriction level of 1 only briefly. Rather than imposing strict lockdowns, Sweden relied on a more voluntary approach to managing mobility.

COVID-19 cases in Sweden remained relatively low until late 2021 when a series of fluctuating spikes occurred. Notably, during this period, Sweden had no stay-at-home restrictions in place, which may have contributed to the rapid rise in cases. However, without any additional restrictions, case numbers subsequently decreased, quickly returning to near-zero levels. This pattern suggests a reliance on natural fluctuation and voluntary compliance, rather than government-imposed restrictions, to manage case surges.





Figure(55c): Double line graph showing mobility variables change over time, new cases and stay-at-home requirement - Libya

Libya was one of the countries with extremely distinguished mobility. Looking at the stay-at-home restrictions graph, Libya initially imposed high restriction levels, reaching level 3 early in the pandemic, which gradually decreased to level 2 for much of 2020 and early 2021. In mid-2021, restrictions were briefly relaxed to level 1 before returning to level 2. By the middle of 2022, all restrictions were lifted, indicating a transition away from formal stay-at-home mandates. The number of cases started to increase significantly just before July 2021. However, during this period, Libya had no restrictions, and it has kept no restrictions despite the high number of new cases. Similarly, it was also during this time that mobility variables started to shoot. It seemed by the second spike that the rising number of new cases did not affect mobility as there were no restrictions.

Figure(55d): Double line graph showing mobility variables change over time, new cases and stay-at-home requirement - Bangladesh

Bangladesh initially imposed moderate restrictions, fluctuating between levels 1 and 2 throughout 2020. In early 2021, restrictions escalated to level 3 in response to rising COVID-19 cases, marking the beginning of the second lockdown in Bangladesh. These restrictions were subsequently reduced to level 2, where they remained until mid-2021 before being further lowered to level 1. By late 2021, all restrictions were lifted, indicating a shift away from strict lockdown measures.

COVID-19 case numbers experienced two significant peaks, around mid-2021 and early 2022. Mobility responded dynamically to the fluctuating restriction levels; for instance, when restrictions were lowered to level 1 in mid-2020, mobility increased rapidly across sectors. Although mobility continued to rise even during moderate restrictions, the rate of increase was slower compared to periods of eased measures. Following the full removal of restrictions at the end of 2021, mobility became more variable but ultimately stabilised near or above baseline levels by 2022, indicating a return to near-normal public activity.

This pattern suggests that while initial restrictions effectively controlled mobility, the gradual easing of restrictions allowed for increased economic and social activity, even as case numbers fluctuated. The steady adaptation of public behaviour in response to relaxed measures reflects a balance between public health protocols and the need to resume normal activity in the face of prolonged pandemic conditions.

4.7 Linear Regression - Global Mobility

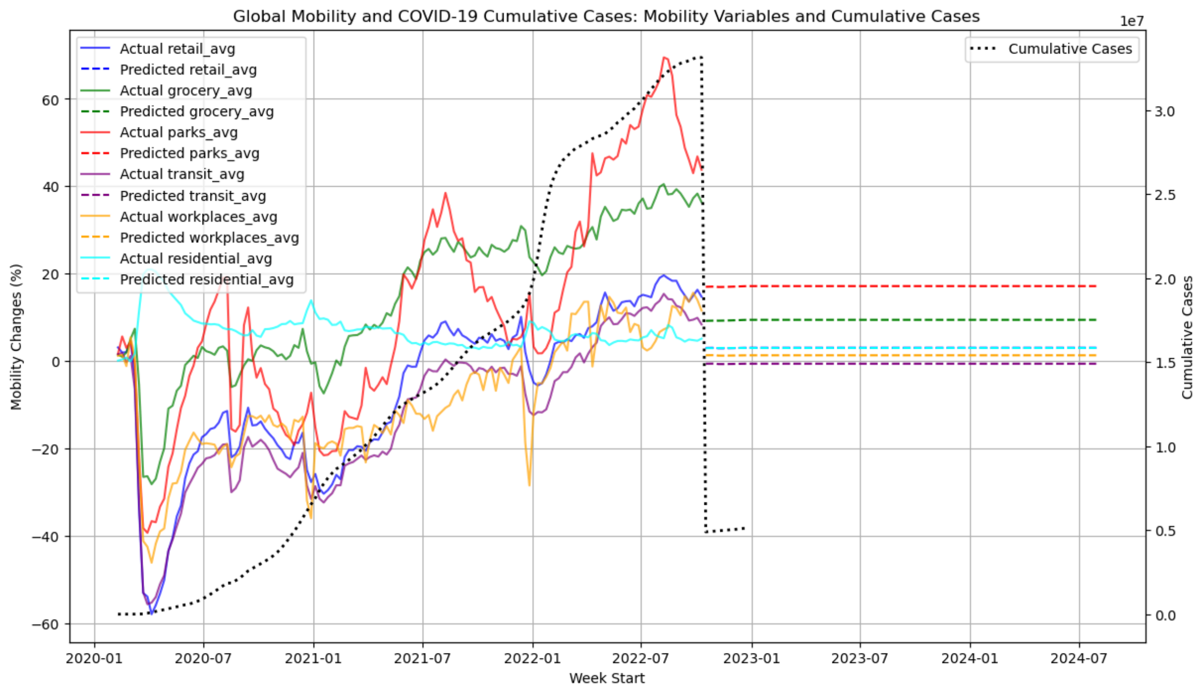


Figure (56): Mobility Trends and Cumulative COVID-19 Cases with Predicted Mobility Values through July 2024

Each sector's mobility is shown as both actual (solid lines) and predicted (dashed lines), providing insight into anticipated trends based on previous data.

The cumulative cases, represented by the dotted black line, display a steady upward trajectory, reflecting the persistent spread of COVID-19. By the end of the actual data in 2022, cumulative cases reach approximately 30 million before declining. Moving into the predicted period, this line plateaus, indicating a possible stabilisation of cases.

Among the mobility variables, parks mobility (red line) exhibits the highest fluctuation and overall mobility change, peaking at around +60% above baseline in 2022. The predicted trend for park mobility suggests it will stabilise near +20% by mid-2024, reflecting a continued but moderated increase above baseline levels.

Grocery mobility (green line) also shows substantial movement, with actual data peaking at approximately +40%. The predicted value for grocery mobility stabilises just below this level at around +10% above baseline, indicating a slight decline from peak values but a sustained elevated level of activity.

Transit mobility (purple line) demonstrates a gradual increase, peaking close to +20% in actual data. The predicted trend shows transit mobility returning to a level just below baseline. This can possibly be attributed to people adjusting to life without transport. However, the negative difference is negligible as it's just under baseline levels.

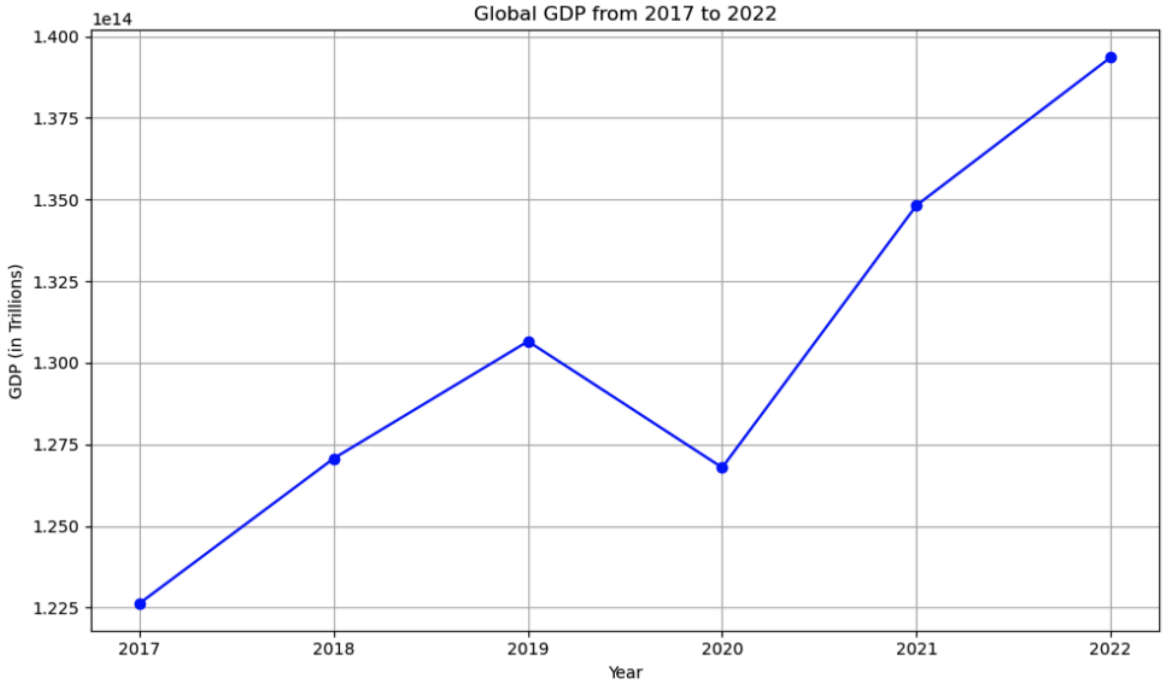
Workplace mobility (yellow line) fluctuates around the baseline in the actual data and is predicted to stabilise slightly above the baseline.

Retail and recreation mobility (blue line) recovers gradually, reaching around +10% by the end of the actual data. The prediction suggests a slight decline, with retail stabilising just below baseline levels by mid-2024.

Finally, residential mobility (cyan line) remains above baseline throughout, peaking at about +10% during periods of high restriction. The predicted trend indicates a return to baseline, reflecting reduced time spent at home as restrictions ease and normal activity resumes.

4.8 Economic and Labour Market Dynamics

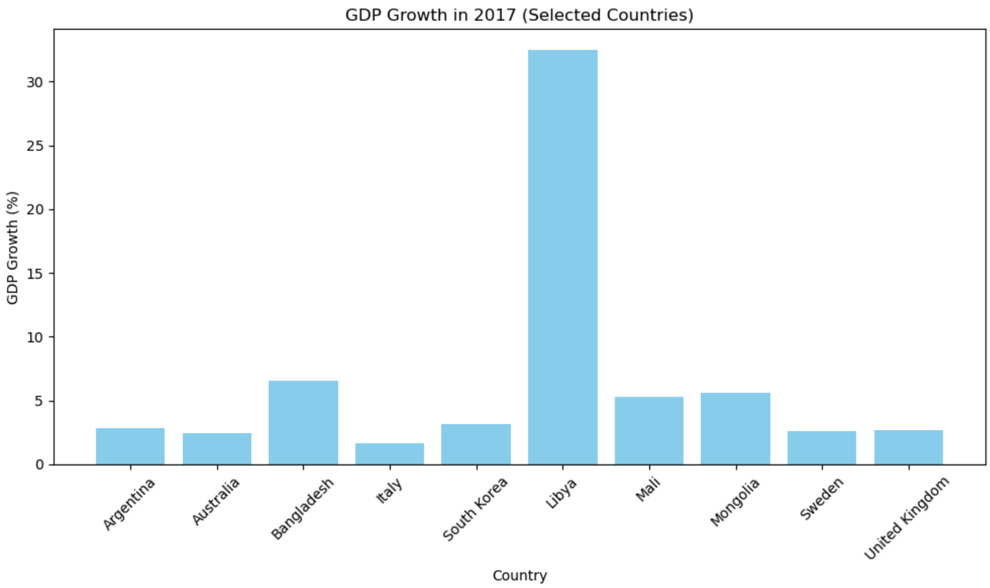
GDP global analysis



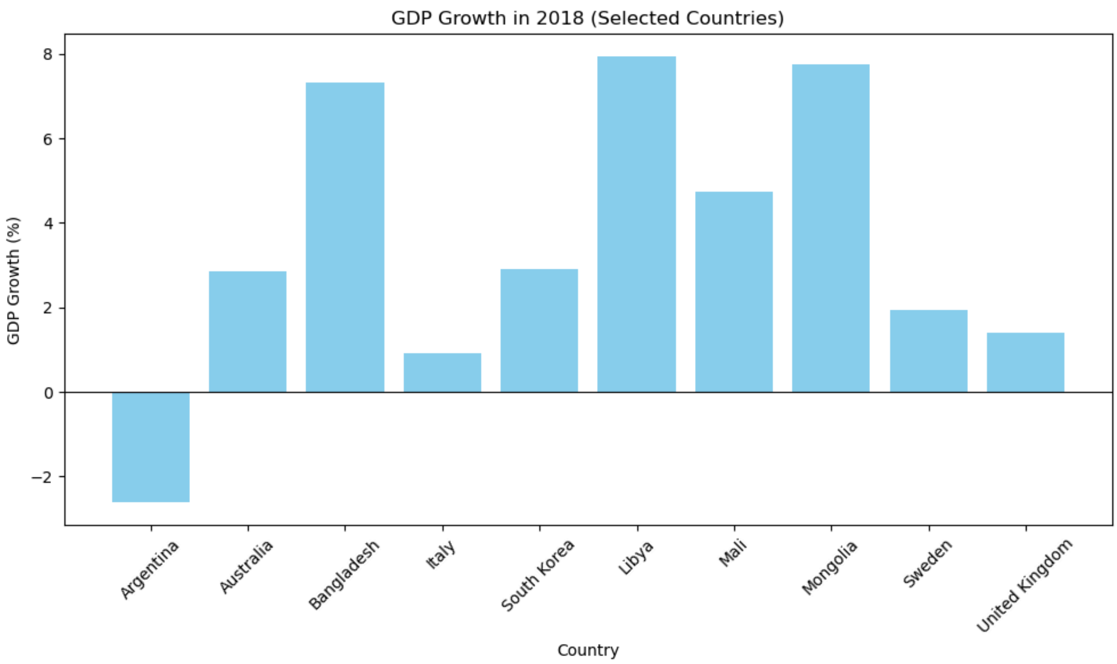
Figure(57): line graph showing GDP in trillions over time

The graph shows a steady increase in GDP from 2017 to 2019, reaching approximately just over $1.3 trillion. A notable decline occurs in 2020 when GDP falls below $1.275 trillion. However, GDP shows a strong recovery in 2021 and continues to rise in 2022, surpassing its pre-pandemic levels to almost $1.4 trillion. This trend indicates resilience in the global economy and a positive outlook for continued growth following the downturn experienced during 2020.

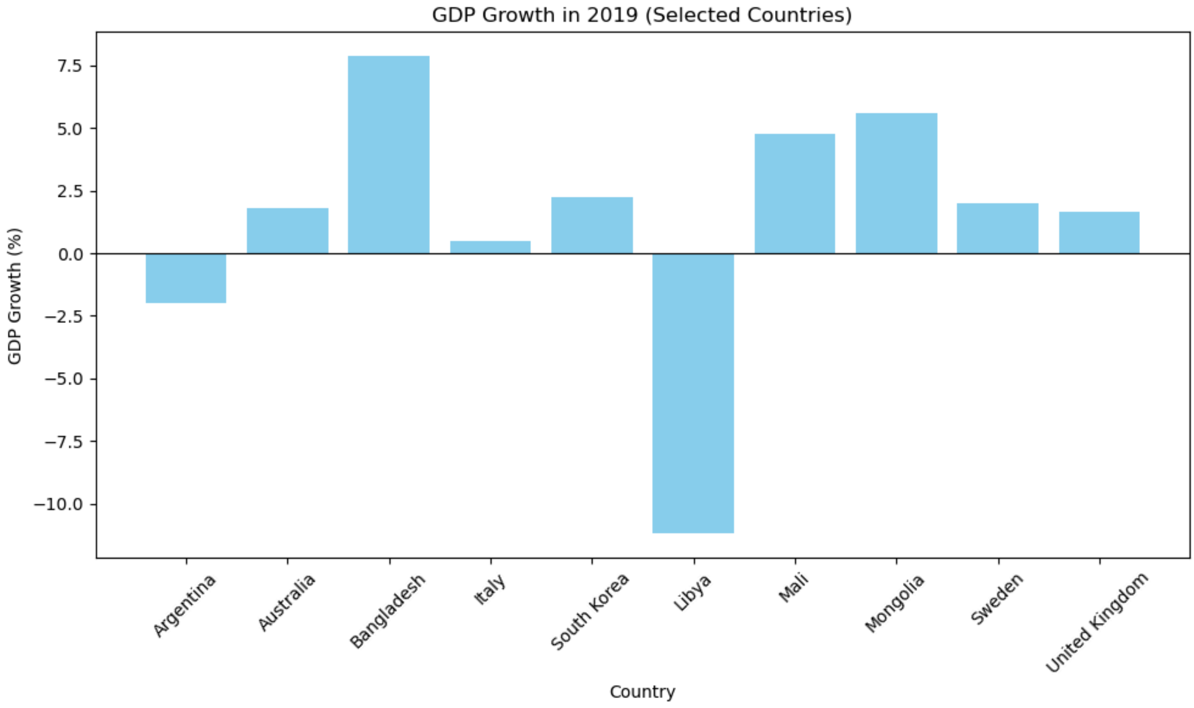
GDP growth for selected countries



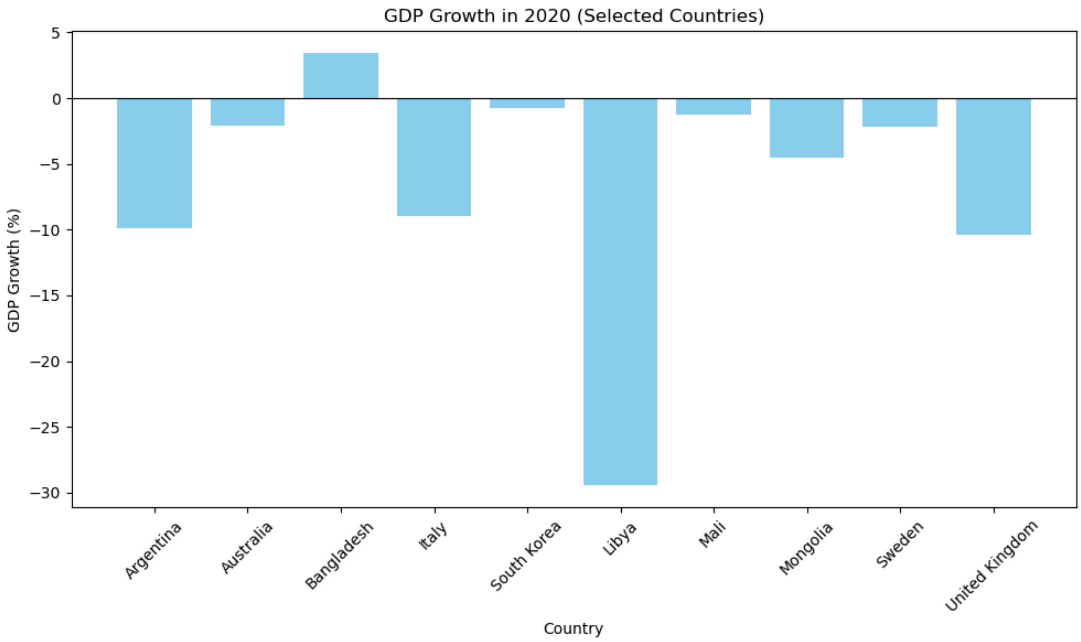
Figure(58a): Bar charts of GDP Growth Trends for Selected Countries (2017)



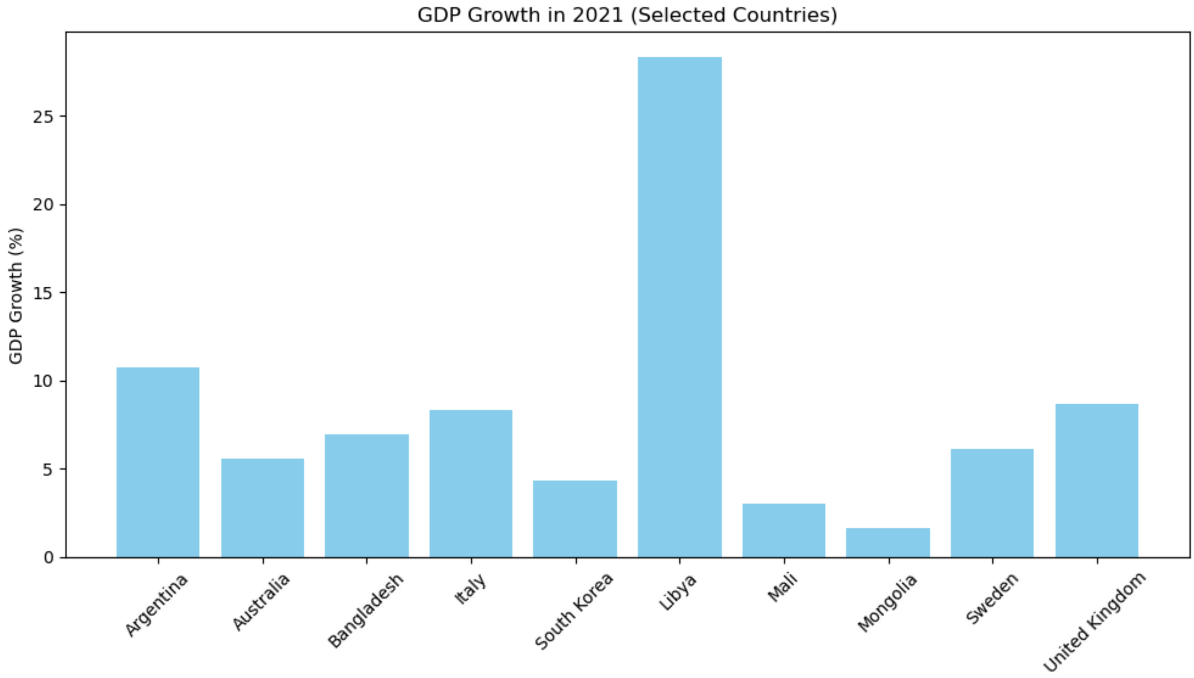
Figure(58b): Bar charts of GDP Growth Trends for Selected Countries (2018)



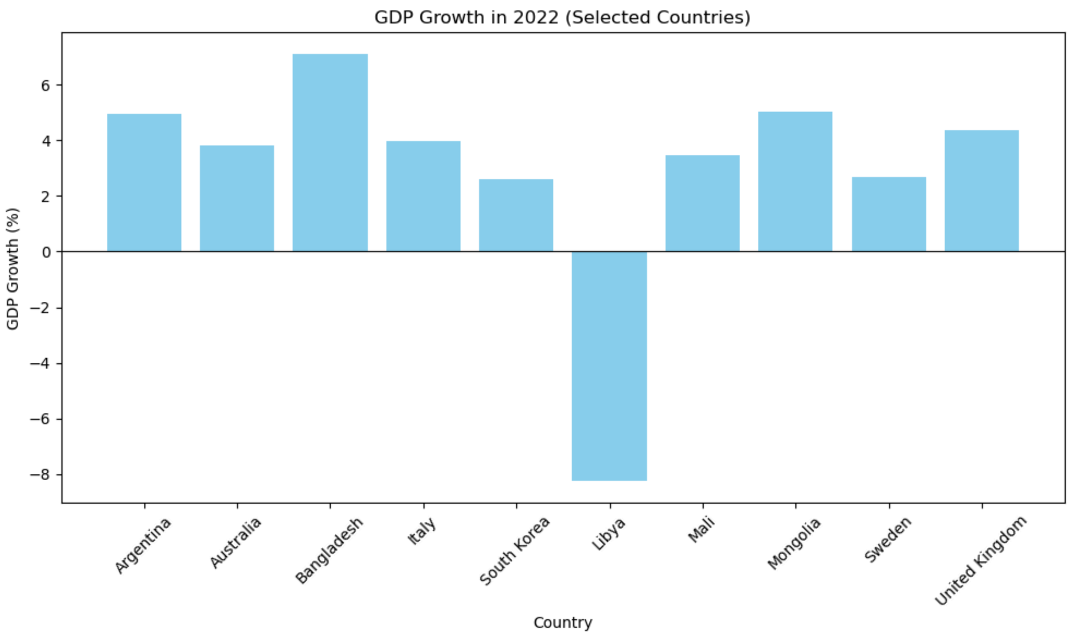
Figure(58c): Bar charts of GDP Growth Trends for Selected Countries (2019)



Figure(58d): Bar charts of GDP Growth Trends for Selected Countries (2020)



Figure(58e): Bar charts of GDP Growth Trends for Selected Countries (2021)



Figure(58f): Bar charts of GDP Growth Trends for Selected Countries (2022)

Libya's GDP fluctuated dramatically, from remarkable growth of 32.5% in 2017 (Figure 1) to severe contractions in 2019 (-11.2%) and 2020 (-29.5%). However, it recovered well in 2021, back up to 28.333% growth. Argentina, meanwhile, struggled with fiscal challenges, experiencing contractions of -2.6% in 2018 and -2.0% in 2019, followed by a steep decline of -9.9% in 2020 due to COVID-19, only to rebound to 10.7% in 2021 as global conditions improved.

Bangladesh consistently demonstrated robust growth, particularly in 2018 (7.3%) and 2019 (7.9%), driven by a strong export sector and remittances. Remarkably, it maintained positive growth of 3.4% during the pandemic in 2020, the only country among the selected to have a positive GDP for the year. Mongolia also displayed solid growth, especially post-pandemic, with a notable rate of 7.0% in 2023, benefiting from its resource-rich economy.

In developed nations, economic performance was steadier but slower, with countries like the UK and Italy experiencing moderate rebounds post-pandemic, particularly in 2021, with growth rates of 8.7% and 8.3%, respectively.

Average GDP Growth Trends for G20 and LDC Countries (2017–2029) (Actual And Forecast)

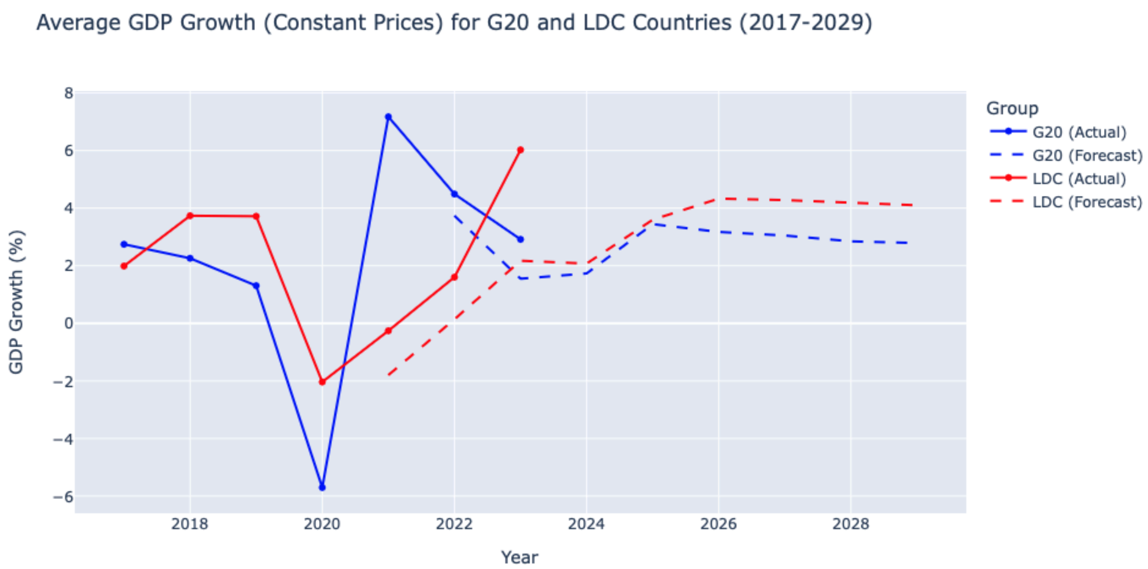


Figure (59): Line graph of projected and actual average GDP Growth for G20 and LDC Countries

G20 countries demonstrated a significant decline in 2020, dropping to nearly -6% due to the global economic impact of the COVID-19 pandemic. Following the sharp contraction, G20 countries experienced a robust recovery, with growth rates peaking in 2021. However, from 2022 onwards, the growth rate stabilises around 2-3%, reflecting a more moderate recovery and alignment with typical growth levels. The forecast suggests a slight decline in the growth trend from 2024, stabilising just above 2% for the remainder of the decade.

The growth trend for LDCs reflects a similar dip in 2020 due to the pandemic, though the decline was less severe than that of the G20. LDCs rebounded strongly in 2021, surpassing G20 growth, with an average growth rate peaking near 6%. The forecast shows that LDC growth is projected to stabilise around 4% post-2023, which is higher than the projected rate for G20 countries. This suggests a potentially stronger growth momentum in developing economies relative to advanced economies, albeit starting from a lower economic base.

Global Unemployment Rate Trends (2019–2029) (Actual and Forecast)

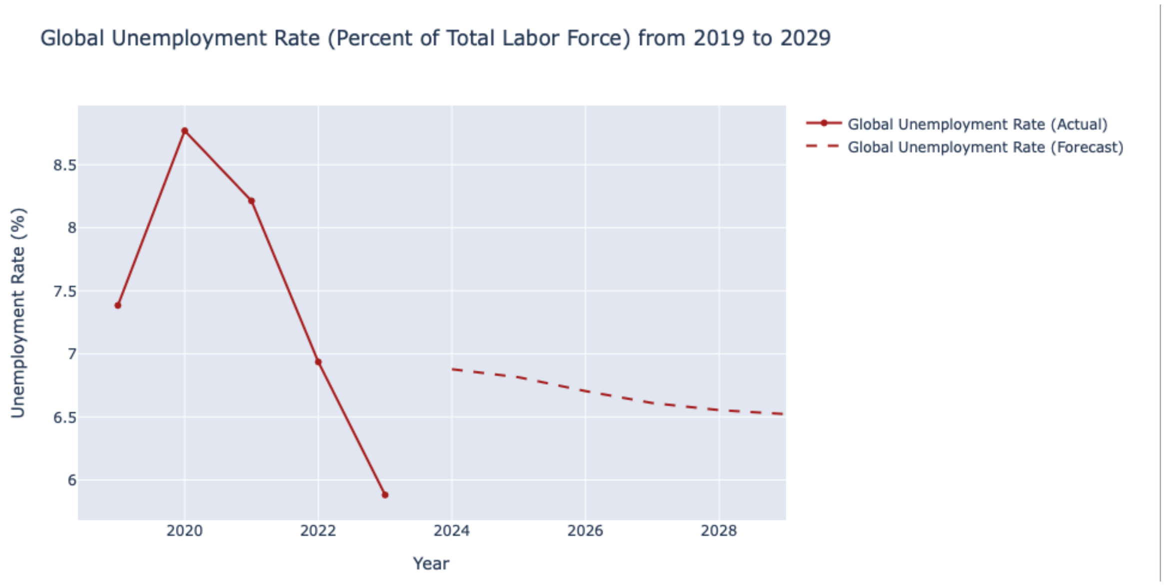
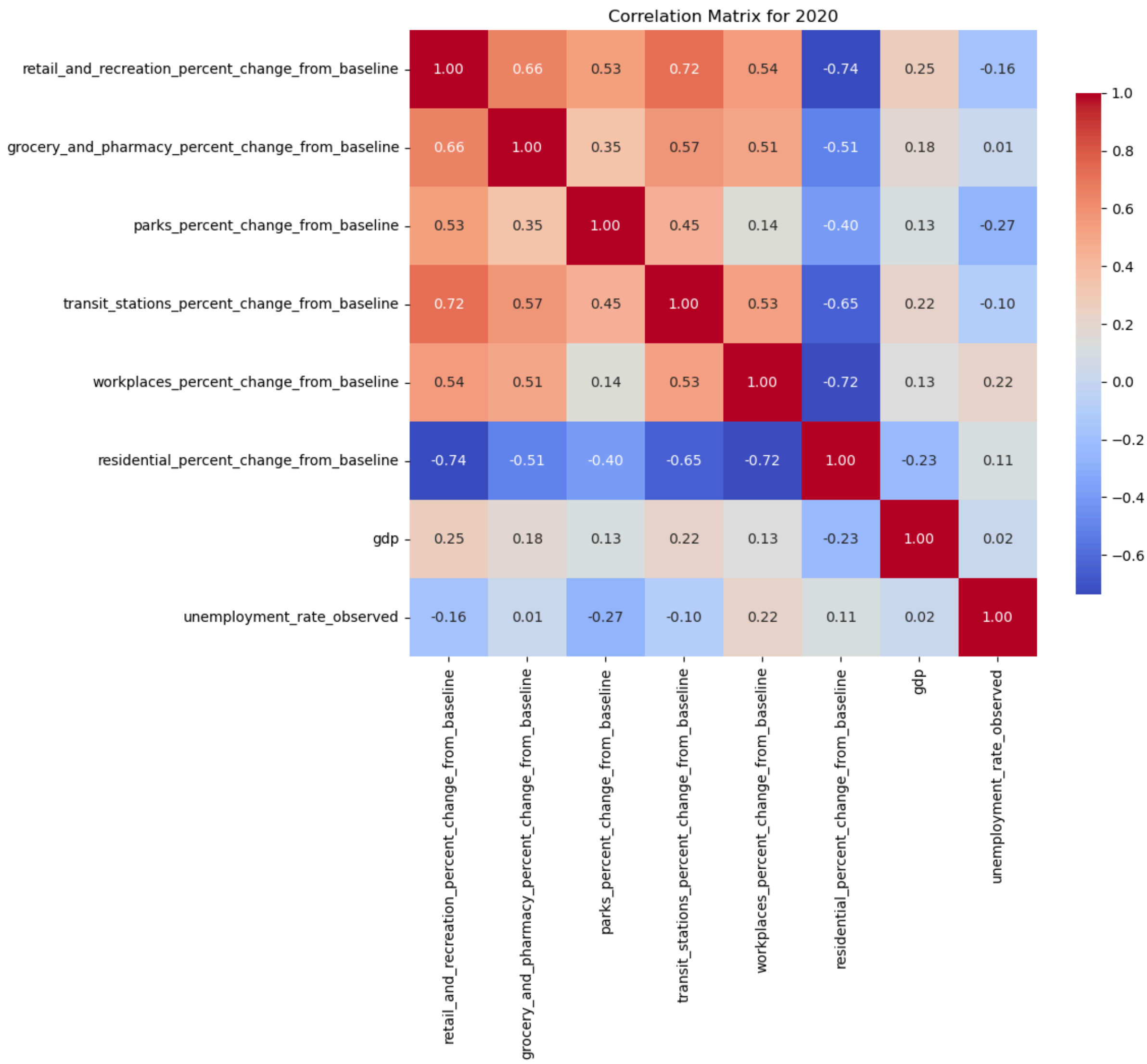


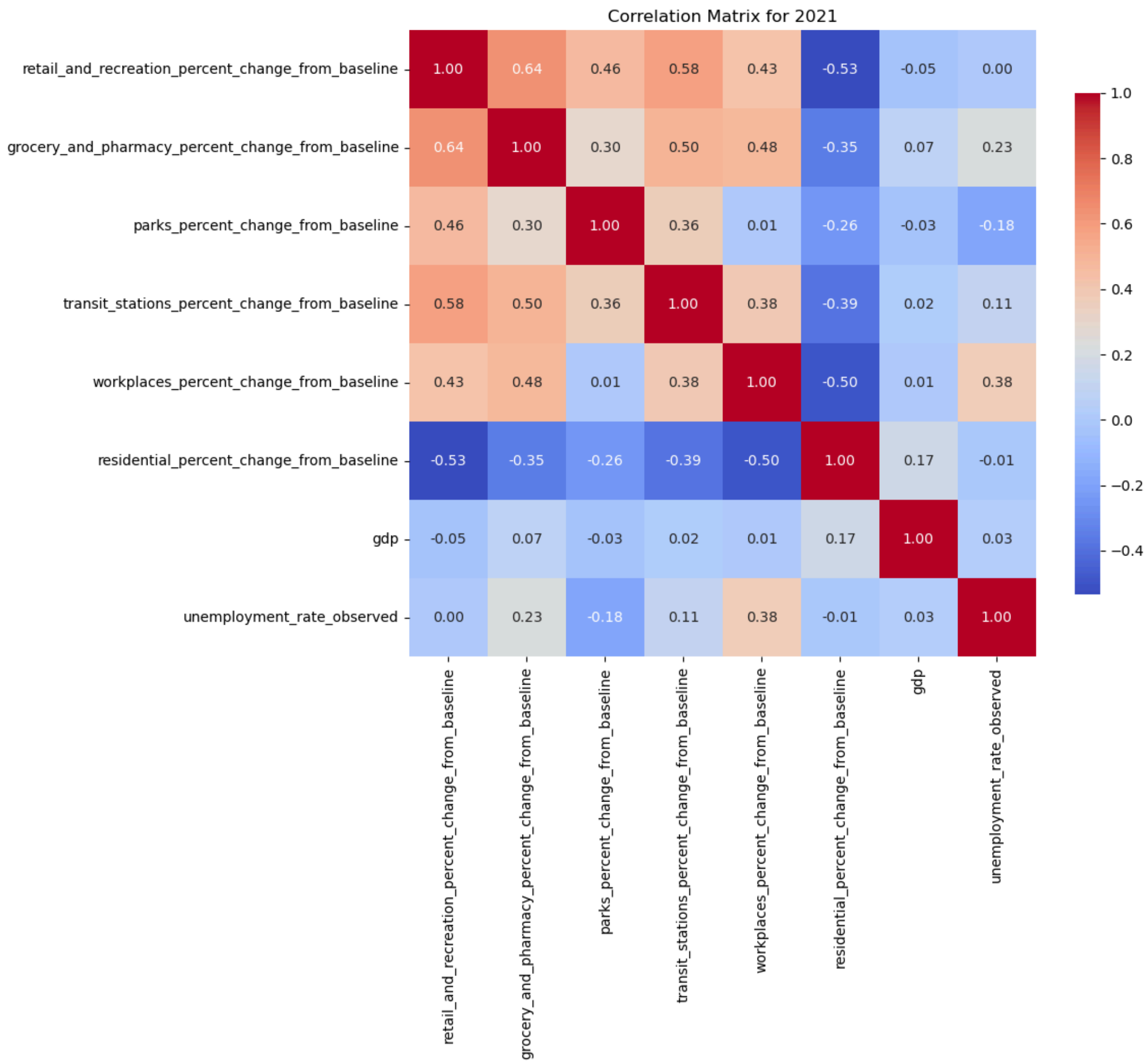
Figure (60): Line graph of projected and actual average unemployment

The global unemployment rate from 2019 to 2023 illustrates the profound impact of the COVID-19 pandemic, followed by a steady recovery and a projected stabilisation. Starting at around 7.5% in 2019, the rate surged to over 8.5% in 2020 due to widespread economic disruptions and job losses. As restrictions eased and economies reopened, unemployment began to decline, reaching below 6% by 2023, signalling a near-return to pre-pandemic levels. Forecasted data from 2024 to 2029 indicates a slight but steady decline, suggesting the global labour market will continue to stabilise around 6%.

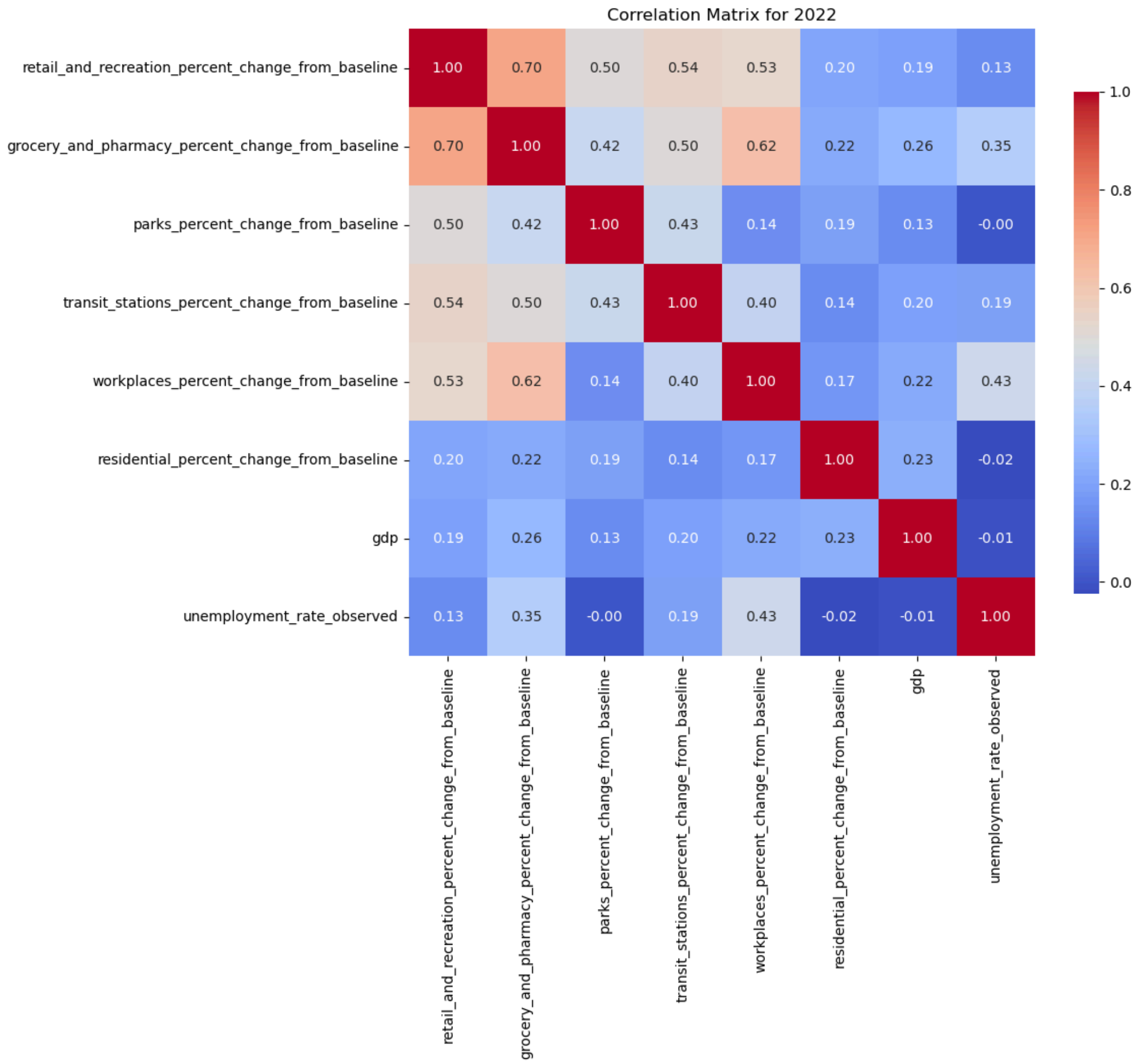
Correlation Matrices of Mobility, GDP, and Unemployment Rates for 2020, 2021, and 2022



Figure(61a): Correlation Matrix 2020



Figure(61b): Correlation Matrix 2021



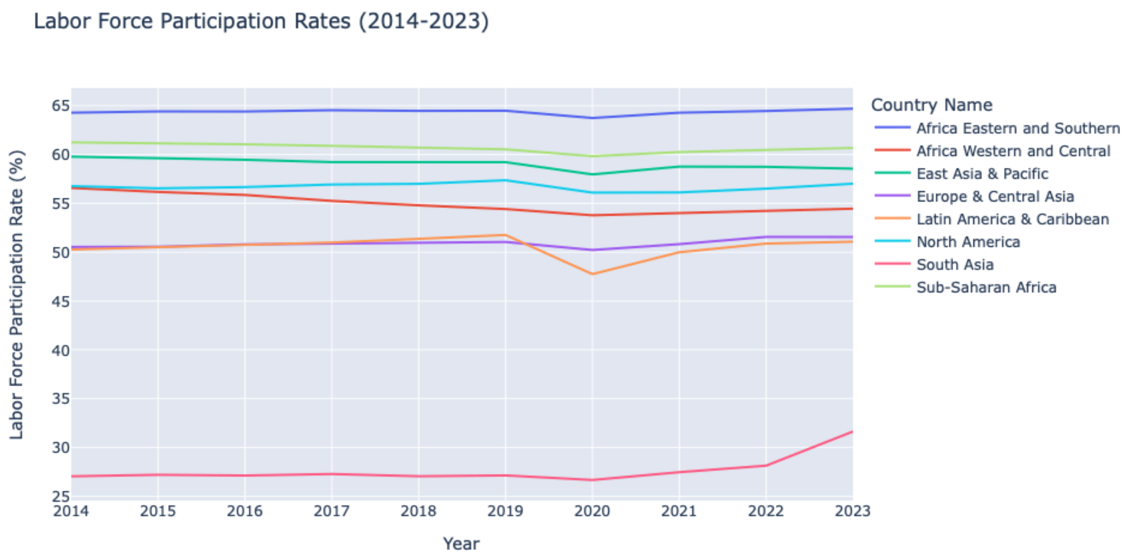
Figure(61c): Correlation Matrix 2022

In 2020, correlations between mobility metrics and GDP were generally positive but modest, with retail and recreation showing the highest (0.25) correlation with GDP, suggesting that economic activity was somewhat aligned with mobility levels amid lockdowns. The relationship between mobility and unemployment was weak, with the highest correlation being workplace (0.22), indicating that changes in mobility had a limited direct impact on employment levels during the initial pandemic shock. The correlation between GDP and unemployment (0.02) was also weak, reflecting the complex economic conditions where GDP contraction did not directly translate to unemployment changes due to varied government support measures.

In 2021, as reopening efforts progressed, the correlation between mobility and GDP decreased further, with the highest being residential at 0.17. This suggests that GDP recovery was less dependent on mobility patterns as economic resilience grew. The correlation between mobility and unemployment saw some minor increases, particularly with the workplace (0.38), indicating potential job recovery in essential sectors. The GDP and unemployment correlation remained weak (0.03), highlighting the ongoing disconnect between output levels and employment recovery.

By 2022, mobility and GDP correlations became stronger, with grocery mobility at 0.26 being the strongest, likely reflecting stable consumer demand rather than direct GDP dependency on mobility. Mobility metrics showed only minor correlations with unemployment, with workplaces and grocery mobility showing slight positive correlations (0.43 and 0.35, respectively), potentially linked to increased job stability in specific sectors. The correlation between GDP and unemployment was near zero (-0.01), suggesting that by this stage, GDP and employment recovery were largely independent of each other and less influenced by changes in mobility. Overall, the matrices reveal a decreasing dependency of GDP and unemployment on mobility patterns.

Labor Force Participation Rates by Region (2014–2023)



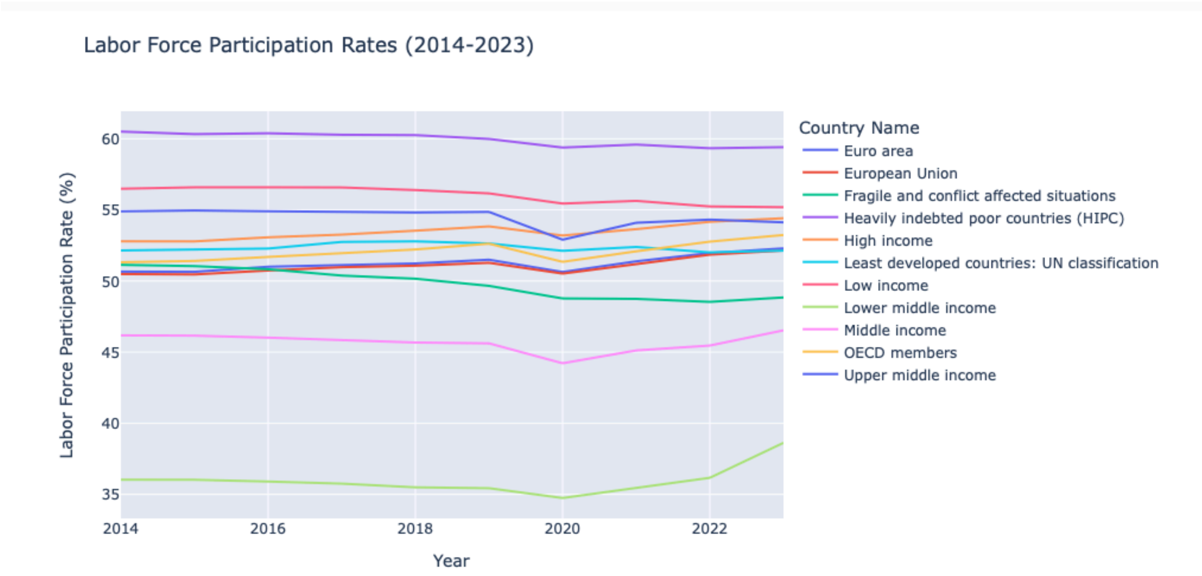
Figure(62): line graph showing Regional Labor Force Participation Rates from 2014 to 2023

Africa, Eastern and Southern, maintained the highest rates, consistently above 64%, peaking at 64.7% in 2023. This region showed stability even during the pandemic, with a slight dip in 2020 to 63.7% but quickly returning to pre-pandemic levels by 2021. Sub-Saharan Africa and East Asia & Pacific also maintained high participation rates, with Sub-Saharan Africa stabilising around 60.7% in 2023 after a minor decline during 2020, while East Asia & Pacific recorded a slight decline to 58.6% by 2023.

Europe & Central Asia and Latin America & Caribbean both experienced modest fluctuations. Europe & Central Asia held steady, with a slight increase from 50.5% in 2014 to 51.6% in 2022, showing resilience amid economic challenges. Latin America & Caribbean, however, faced a sharp drop in 2020, reaching 47.8%, likely due to the pandemic, but partially rebounded to 51.1% by 2023.

North America demonstrated a gradual increase, rising from 56.8% in 2014 to 57.0% in 2023, with only a slight dip during 2020. South Asia, while having the lowest labour force participation, showed significant growth, increasing from 27.0% in 2014 to 31.6% in 2023, with an accelerated rise post-2020.

Labor Force Participation Rates by Economic Classification (2014–2023)



Figure(63): line graph - Labor Force Participation Rates from 2014 to 2023 by Income and Economic Classification

Heavily indebted poor countries (HIPC) maintained the highest labour force participation rates, consistently above 59%, with a slight decline during the pandemic in 2020, reaching 59.4% by 2023. Low-income countries also exhibited relatively high participation rates, though they experienced a gradual decrease over the decade, dipping from 56.5% in 2014 to 55.2% in 2023.

In contrast, lower-middle-income countries had the lowest participation rates, with a downward trend until 2020, after which there was a gradual increase, reaching 38.6% in 2023. Middle-income countries showed a similar pattern of decline until 2020, with a recovery in recent years, reaching 46.5% in 2023. This pattern likely reflects the impact of the pandemic followed by recovery as economies adjusted.

Fragile and conflict-affected situations displayed a consistent decline from 51.1% in 2014 to 48.8% in 2023, reflecting ongoing challenges in workforce stability within these regions. Meanwhile, the European Union and the Euro area demonstrated stable and gradually rising participation rates, reaching approximately 52% by 2023, which could indicate sustained workforce engagement within these developed regions.

4.8 Gender gap analysis

Trends in Global Gender Pay Gap (2015–2024)

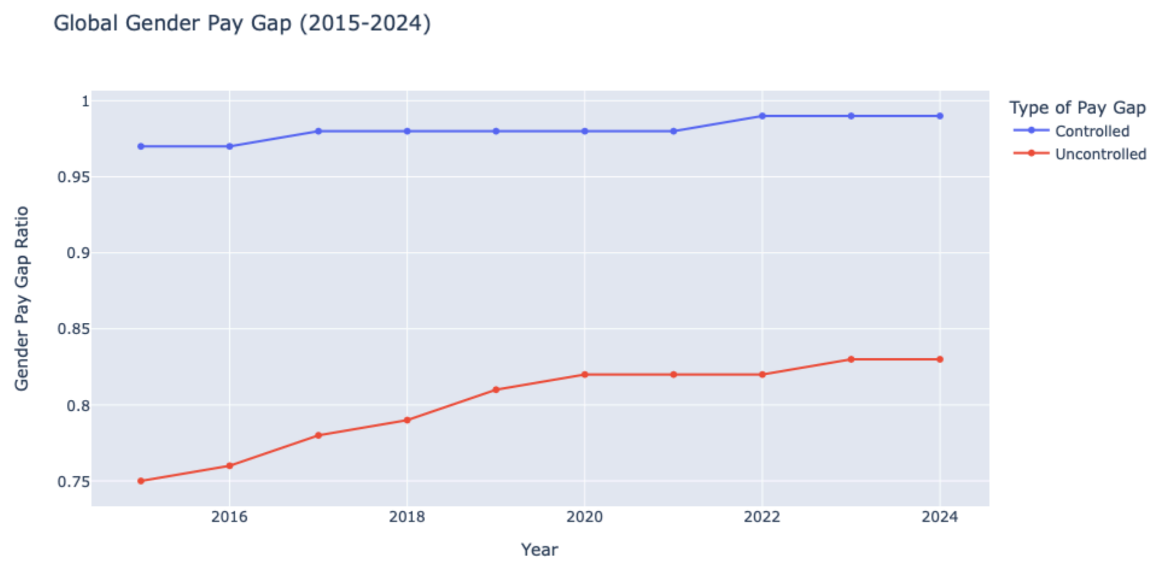


Figure (64): Line graph showing controlled and Uncontrolled Gender Pay Gap Ratios from 2015 to 2024

The controlled gender pay gap ratio, which accounts for factors such as job title, education, and experience, remains relatively stable and close to 1.0, indicating near parity when these factors are considered. This ratio has only slightly increased, reflecting limited improvements over the decade.

In contrast, the uncontrolled gender pay gap ratio, which does not adjust for these variables, started around 0.75 in 2015 and showed a gradual upward trend, reaching approximately 0.83 by 2024. Although there has been improvement, the gap remains significant, suggesting that women are, on average, still paid less than men in the workforce as a whole. The long-term trend in the uncontrolled gap points to a slow reduction in inequality, but the persistent difference between the controlled and uncontrolled ratios indicates structural challenges that continue to affect women's earnings on a global scale.

Global Trends in Unemployment, GDP, and Gender Pay Gap (2015–2029)

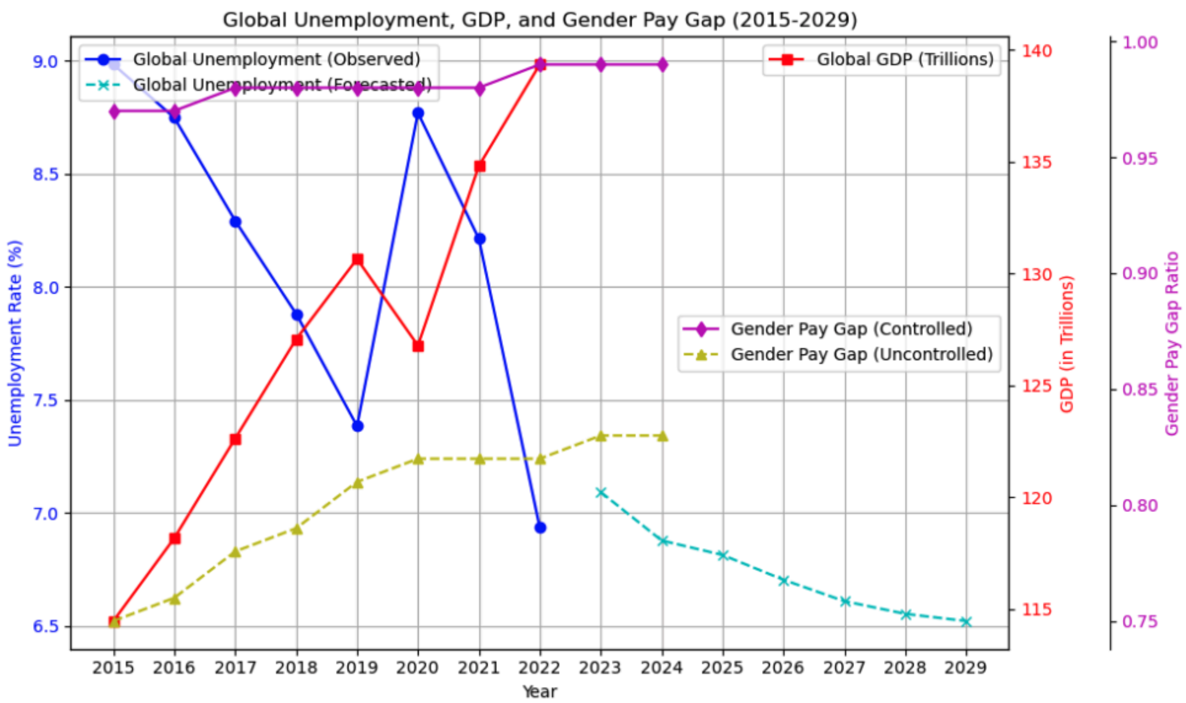


Figure (65): Global Unemployment Rate, GDP (Trillions), and Gender Pay Gap Ratios from 2015 to 2029

The global unemployment rate (observed) experienced notable fluctuations. In 2015, it stood at around 9%, followed by a decline to below 7.5% in 2019, peaking in 2020 at around 8.8% due to the COVID-19 pandemic's impact on the global labour market, followed by a steep decline in 2021. Forecast data predicts a gradual decline in the unemployment rate, potentially reaching below 7% by 2029, indicating anticipated stabilisation in global employment.

Global GDP, shown in trillions, displays a steady upward trend from approximately $115 trillion in 2015 to $140 trillion by 2022. The general trend for GDP is that it has been increasing. The steady increase in GDP suggests economic resilience despite short-term disruptions, with a continued trajectory of growth.

The gender pay gap data shows that the controlled gap remains consistently close to 1.0, indicating near parity when factors like role and experience are accounted for. Although the rate of growth for the controlled gender pay gap has remained relatively stagnant when compared to the uncontrolled gap, it lags behind. The uncontrolled gender pay gap has increased significantly over the years; however, as of 2022, it has just exceeded 0.80, reflecting persistent disparities in pay between genders in the broader labour market. The slight increase in the uncontrolled gap ratio over time suggests slow improvement, but the gap remains substantial, emphasising the need for ongoing efforts to close this disparity.

Workplace Gender Gap Worldwide (2024) by Type

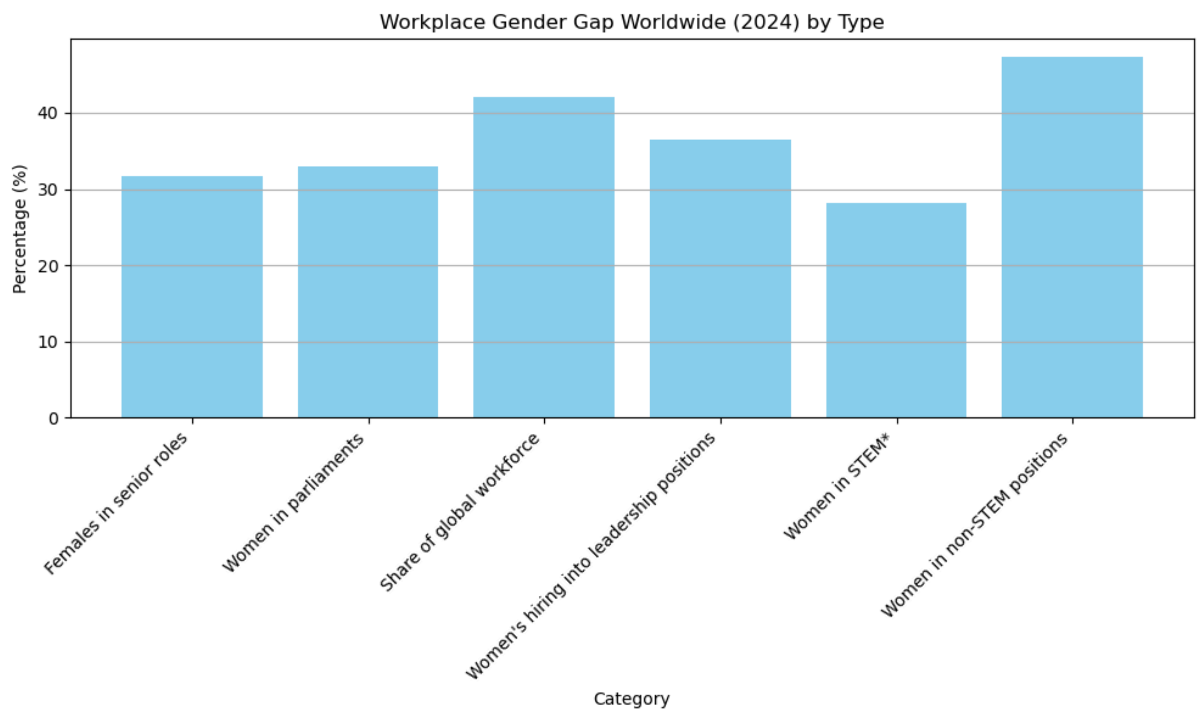


Figure (66): Bar plot of workplace-related gender gap 2024

Women in non-STEM positions represent the highest percentage at approximately 45%, suggesting greater gender inclusivity in these fields. In contrast, the representation of women in STEM roles remains lower at around 25%, underscoring the ongoing gender imbalance in science, technology, engineering, and mathematics fields.

Women's hiring into leadership positions and the share of the global workforce held by women are each around 40%, indicating progress toward gender diversity in leadership and workforce participation but still below parity. Women in senior roles and women in parliaments each hover around 35%, reflecting limited but increasing participation in high-level and governmental roles. Overall, the distribution shown in this figure underscores both achievements and areas where gender equality continues to require focused efforts, particularly in STEM and leadership roles.

4.10 Gender Pay gap prediction

Predicted Global Gender Pay Gap (Uncontrolled) by Mobility and GDP Scenarios (2023-2032)

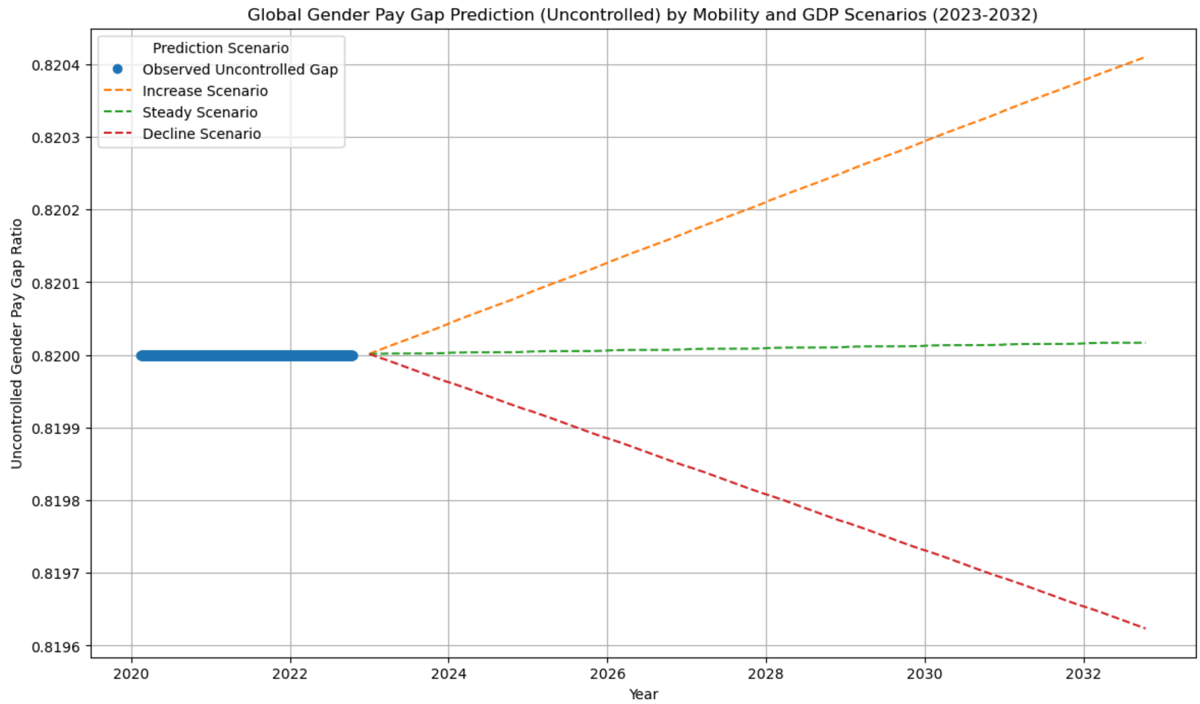


Figure (66a): Line graph of predicted gender pay gap uncontrolled (Mobility variables and GDP)

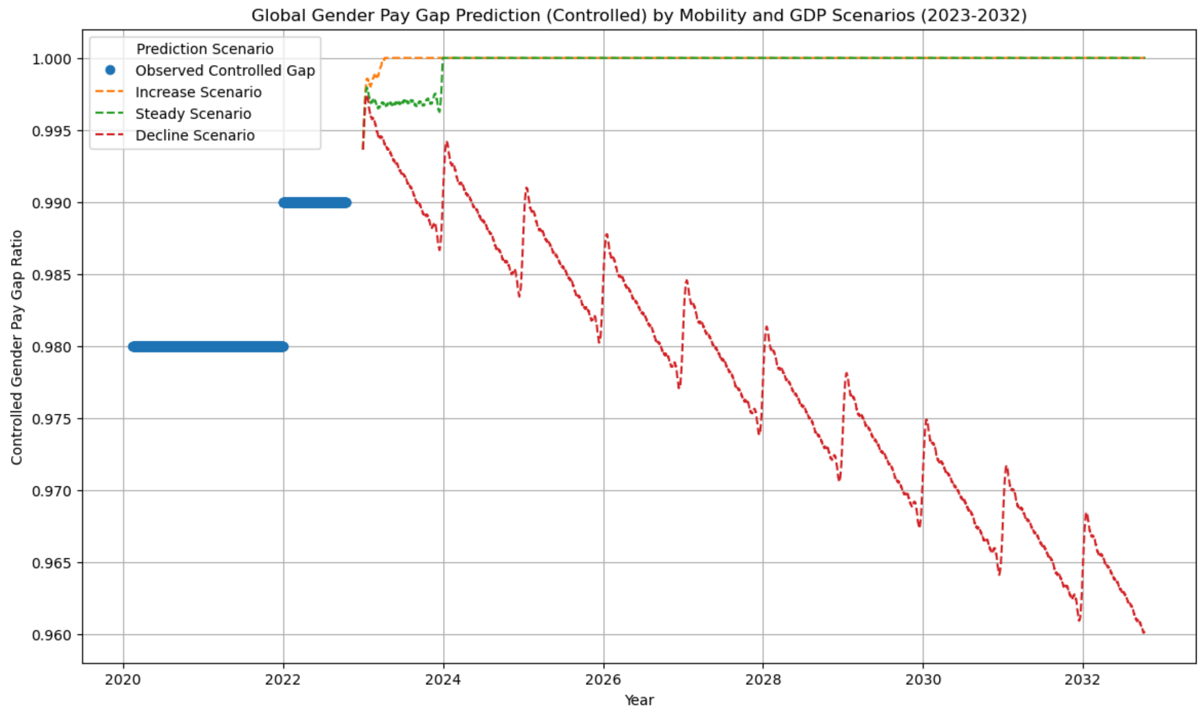


Figure (66b): Line graph of predicted gender pay gap controlled (Mobility variables and GDP)

The observed uncontrolled gap remains stable at approximately 0.8200 until 2022. In the Increase Scenario, where mobility and GDP are projected to rise, the uncontrolled gap slightly widens, reaching just above 0.8204 by 2032. Conversely, the Steady Scenario suggests that if mobility and GDP remain constant, the uncontrolled gap maintains a similar level to the observed values, indicating little fluctuation. In the Decline Scenario, a decrease in mobility and GDP leads to a gradual reduction in the uncontrolled gender pay gap, potentially reaching around 0.8196 by 2032. This indicates that while mobility and GDP do have an influence, the effects on the uncontrolled gap are relatively modest.

In contrast, the controlled The Increase Scenario depicts a slight upward trend, with the controlled gap peaking near 1.000, since the global gender pay gap is currently at 0.99, it's not relatively far from gender pay equality in the controlled sector before stabilising. The Steady Scenario demonstrates that constant mobility and GDP levels lead to a stable controlled gap, closely following the observed trends. However, the Decline Scenario reveals significant volatility in the controlled gender pay gap, with cycles that can dip as low as 0.960. This suggests that the controlled gap is more sensitive to changes in mobility and GDP, particularly in declining economic conditions.

In summary, the uncontrolled gender pay gap exhibits a relatively stable response to fluctuations in mobility and GDP, with minor variations across scenarios. In contrast, the controlled gender pay gap displays greater volatility and sensitivity, indicating that it is more responsive to economic changes. This suggests that while efforts to improve mobility and economic conditions are crucial for addressing both gaps, the controlled gender pay gap may require more targeted interventions to stabilise and improve gender pay equity, particularly during economic downturns.

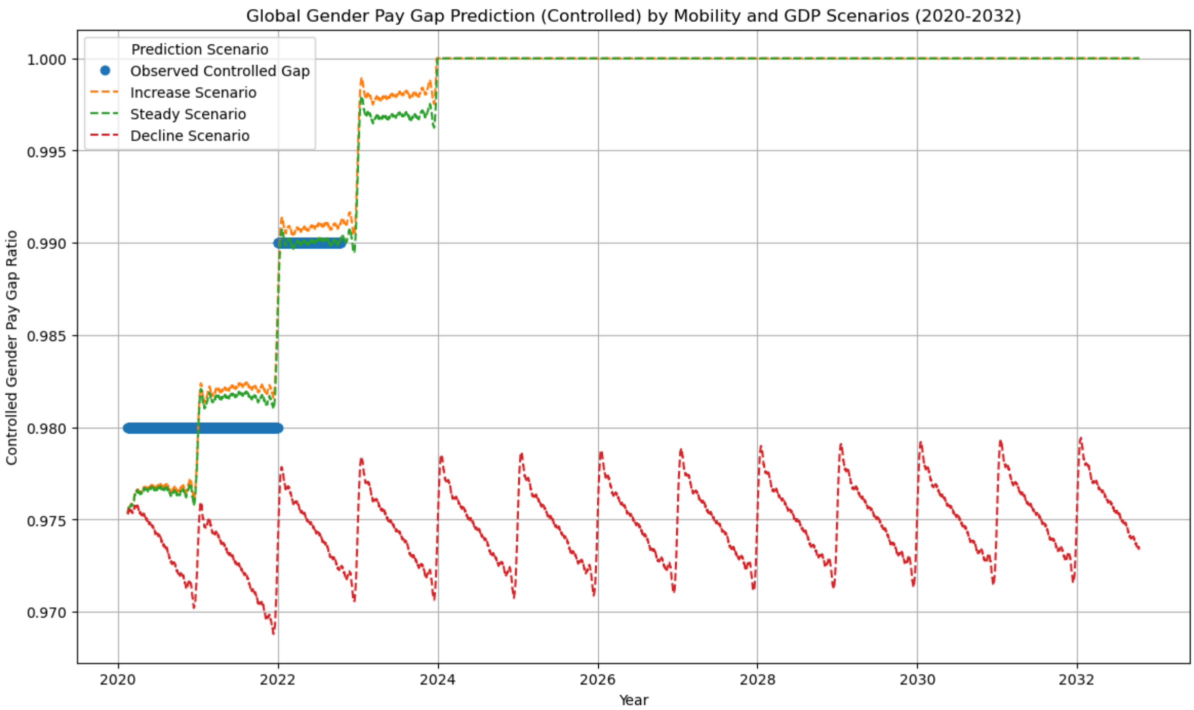


Figure (66c): Line graph of predicted gender pay gap controlled (Mobility variables and unemployment)

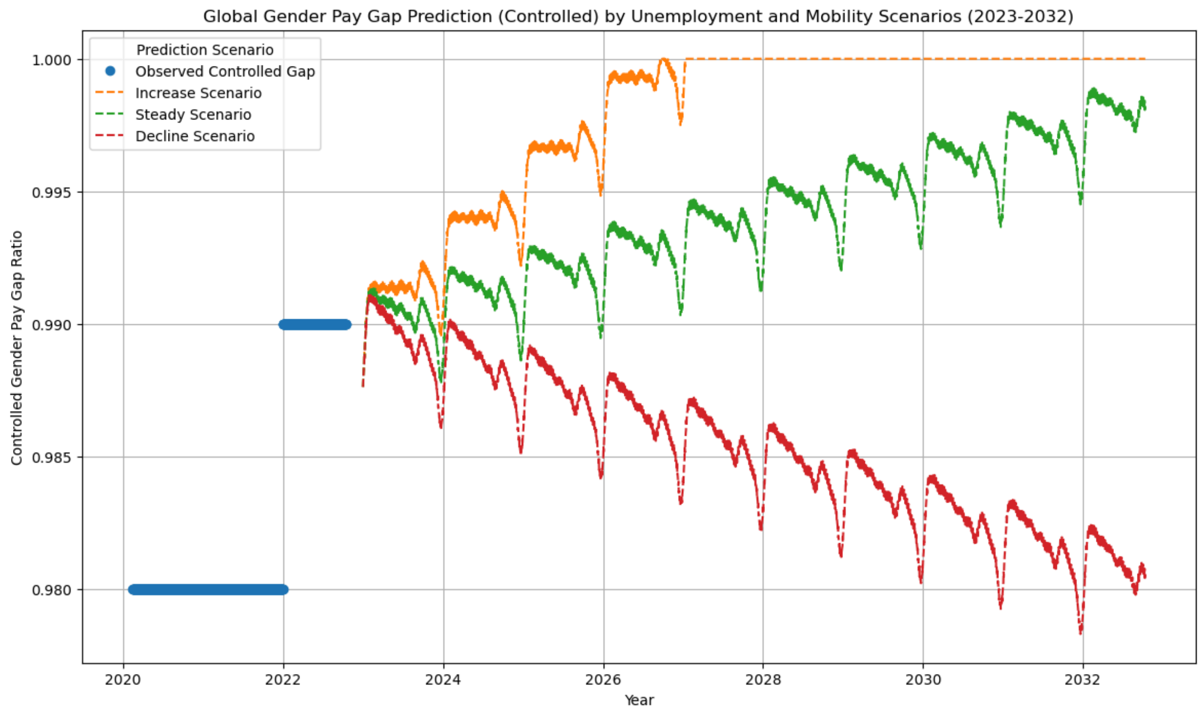


Figure (66d): Line graph of predicted gender pay gap uncontrolled (Mobility variables and unemployment)

The observed uncontrolled gender pay gap remained stable at around 0.8200 until 2022. The Increase Scenario (orange dashed line) forecasts a gradual rise in the uncontrolled gender pay gap, suggesting an increase in mobility and economic activity to 0.82075, although the increase is not substantial for 10-year periods. The Steady Scenario (green dashed line) implies that maintaining current levels of mobility and unemployment will keep the uncontrolled gap relatively constant over the forecast period. In contrast, the Decline Scenario (red dashed line) anticipates a decrease in the uncontrolled gender pay gap, indicating that a decline in these factors could contribute to increasing disparities, although the overall effect appears minimal.

The controlled gender pay gap fluctuates between approximately 0.990 and 1.000 until 2022. In the Increase Scenario (orange dashed line), the controlled gap shows a modest upward trend and expects to achieve gender pay equality in the controlled sector by 2027. The Steady Scenario (green dashed line) reveals a more stable trend, suggesting that constant conditions will keep the controlled gap steady, aligning closely with observed values, although gender pay equality won't be achieved within the 10-year prediction period. However, the Decline Scenario (red dashed line) exhibits significant oscillation, indicating that decreasing mobility and economic conditions can lead to the gender pay gap falling below 0.980.

5. Discussions

5.1 Chapter brief

This chapter examines the results in relation to the study's objectives, comparing findings with existing literature and exploring the implications of the study on policy and future research. Confidence in the results is evaluated based on study methods rigour and data quality, highlighting strengths and limitations. The study's recommendations centre on addressing gender pay disparities caused by COVID-19's impact on mobility and economic outcomes.

5.2 Objective Analysis

Objective 1: Analysing Changes in Mobility Patterns During the COVID-19 Pandemic

Discussion of Findings:
The analysis revealed significant reductions in mobility across various categories at the onset of the pandemic, with retail and recreation experiencing the sharpest declines—nearly 60% globally. In contrast, residential mobility consistently rose as stay-at-home mandates led people to spend more time at home.

An examination of individual countries provides a clearer view of how varied public health measures impacted mobility. For example, Sweden, which adopted a relatively lenient approach with fewer restrictions, displayed a moderate reduction in mobility across sectors compared to countries with strict lockdowns. In Sweden, retail and recreation mobility showed smaller declines and recovered more quickly, reflecting the country's approach to maintaining social activities under certain health protocols rather than enforcing full lockdowns. This approach contrasts sharply with Italy, where strict, prolonged lockdowns led to a dramatic drop in mobility, especially in parks and workplaces. Italy's recovery in these sectors was slower, underscoring the effect of stringent policies on mobility trends.

Interestingly, LDCs showed faster recovery across all sectors compared to G20 countries, as seen in the mobility trends for parks and grocery sectors, which normalised by mid-2021 in many LDCs but lagged in G20 regions *(Figure 31*). This is likely attributable to stricter public health measures and remote work infrastructure in developed economies, contrasting with the economic necessity for physical attendance in LDCs.

For example, Bangladesh saw a rapid normalisation of grocery mobility by mid-2021, reflecting economic imperatives that required a quicker return to commercial sites. Despite official advisories, many people in Bangladesh resumed activities due to income reliance on daily wages. Similarly, Nigeria experienced a quick rebound in transit and retail mobility, highlighting the limited feasibility of sustained restrictions in economies where informal work dominates.

This divergence in recovery timelines, as observed in *Figure 31*, underscores the role of economic infrastructure in influencing mobility. In G20 nations, where remote work is more feasible, mobility remained constrained for longer, particularly in workplaces and transit stations. Conversely, in countries like Kenya and Ghana, where remote work is less accessible, and many rely on physical attendance, mobility rebounded sooner despite public health risks.

Comparison to Literature:
The observed results are consistent with (Bonaccorsi et al., 2020), who documented slower mobility recovery in high-income countries due to strict lockdowns and effective public health enforcement. Abu-Rayash and Dincer (2021) also reported severe reductions in mobility in developed countries, attributing this to extensive remote work policies. However, this study adds depth by focusing on sector-specific timelines and resilience patterns across individual countries. The quicker recovery in variables such as parks and grocery sectors in countries with looser restrictions, like Sweden, shows how essential and outdoor activities can bounce back more easily. However, this trend does not apply universally. In Libya, despite imposing strict lockdowns, mobility remained high. This exception is likely due to the country's ongoing refugee and political crisis, which forced people to move frequently to access essential resources, healthcare, and humanitarian aid (Iwendi et al., 2021). This highlights the complexity of mobility patterns, which are influenced not only by restrictions but also by social and economic pressures unique to each country.

Implications:
These findings suggest that future public health policies could benefit from a nuanced, sector-based approach. Countries with significant informal sectors or limited remote work options may need flexible restrictions that allow for essential services and outdoor activities to operate with safety protocols rather than imposing full closures. For countries with more robust remote work facilities, targeted lockdowns in high-contact sectors could effectively balance public health with economic

stability. The results indicate that controlled access could be an alternative to complete lockdowns in future crises, allowing for a balanced response that mitigates both health and economic impacts.

Potential Changes:
Future studies could expand on these insights by conducting detailed country-specific analyses within both LDC and G20 groups. This would allow for a more comprehensive understanding of how varied public health responses and economic structures influenced recovery. Additionally, incorporating data on vaccination rates and public health campaigns may clarify regional differences in mobility recovery, especially as vaccinations have become a crucial factor in managing pandemic-related restrictions.

Objective 2: Examining the Impact of Mobility Restrictions on the Labor Market and Economic Outcomes

Discussion of Findings: The study revealed that sectors with high remote work potential, particularly in G20 nations, had fewer disruptions, as evidenced by stable workplace mobility in the tech and finance sectors. In LDCs, where informal economies predominate, rapid recovery in workplace mobility was essential, as physical attendance was necessary for income generation. The results show that transit and workplace mobility in G20 countries lagged behind that of LDCs (*Figure 28*), highlighting differing economic resilience driven by structural and policy factors.

The correlation heatmaps from 2020 to 2022 further illustrate these relationships. In 2020, mobility and GDP correlations were moderate across most variables, with the highest correlation (0.25) seen between retail and recreation mobility and GDP, indicating that economic activity in these sectors was somewhat aligned with mobility levels. Meanwhile, the relationship between mobility and unemployment was weak, likely due to government support measures that cushioned initial unemployment impacts. As recovery progressed in 2021 and 2022, the correlation between mobility and GDP declined, while correlations with unemployment increased slightly, particularly with workplace mobility in 2022 (0.43).

Comparison to Literature: These findings align with (Dingel and Neiman, 2020), who documented smoother labour market adaptations in sectors with remote work in developed economies. The study of (Loayza and Pennings, 2020) similarly emphasised that low-income countries, which rely on informal labour markets, struggled to adopt remote work measures, aligning with this study’s results showing quicker physical returns in LDCs. The results add further detail by showing that even within developed economies, variability in sectors exists, reflecting differences in workplace policies and infrastructure availability.

Implications: These findings indicate that future public health policies could benefit from adapting lockdown measures to account for the informal sector in LDCs, potentially allowing limited operation of critical in-person sectors under strict health guidelines. Developing digital infrastructure in LDCs may also help build resilience in future pandemics, facilitating remote work where feasible.

Potential Changes: The analysis could be further explored by examining individual sectors within each country to gain insights into the specific characteristics of resilience across industries. Additionally, incorporating information on digital infrastructure and remote work policies could enhance the understanding of labour market responses.

Objective 3: Investigating the Effects of Mobility Patterns on Gender Pay Disparity

Discussion of Findings: The analysis of gender pay disparity highlighted significant challenges for women, particularly in sectors like retail and hospitality, which were severely affected by mobility restrictions. The uncontrolled gender pay gap widened considerably during peak lockdowns, especially in LDCs, where sectors employing a high proportion of women experienced more prolonged labour disruptions. Figures in the results section, such as *Figure 66*, illustrate that while the controlled gender pay gap remained somewhat stable, the uncontrolled gap decreased very slightly during the pandemic.

Comparison to Literature: These findings are consistent with Alon et al. (2020), in which the study observed heightened economic vulnerability for women during the pandemic, as female-dominated sectors were less adaptable to remote work. The study of (Tavares, n.d.) similarly identified an increased gender gap in labour force participation, particularly in countries with limited economic protections for women. This study extends these findings by demonstrating that the gender pay gap in LDCs was exacerbated by a lack of support in high-contact sectors, an aspect less explored in prior research.

Implications: The findings underscore the importance of targeted interventions in sectors with high female employment, particularly during economic crises. Financial relief and flexible work policies tailored for women-led industries could mitigate these disparities. The study suggests that governments should incorporate gender-responsive policies in recovery planning to prevent widening inequalities during future crises.

Potential Changes: Future studies could incorporate additional data on caregiving responsibilities and access to childcare to further clarify the pandemic's impact on women's economic opportunities. Including an analysis of male-dominated sectors would also provide a more balanced view of gender dynamics in pandemic recovery.

Objective 4: Predicting Future Trends in Gender Pay Disparity and Labor Market Inequalities

Discussion of Findings: The predictive analysis indicates that, without targeted interventions, the gender pay gap is likely to persist or widen even with economic recovery. Under the Increase Scenario, the uncontrolled gap could reach 0.8204 by 2032, reflecting a continued disparity in sectors affected by the pandemic (Figure 66a). The Decline Scenario shows an increase in the gap. The stability observed in the controlled gap across scenarios highlights that structured interventions can mitigate widening disparities, especially when gender-sensitive policies are introduced alongside economic recovery efforts.

Comparison to Literature: These findings build on (Hupkau and Petrongolo, 2020), who emphasise that economic recovery alone is insufficient to close gender inequalities without dedicated gender-responsive measures. Similarly, the study of (Tavares, n.d.) noted that labour market recoveries focusing solely on job creation tend to worsen existing gender gaps. This study contributes further by showing that the uncontrolled gender pay gap is particularly susceptible to economic shifts in gendered sectors, suggesting that even robust economic growth may fail to reduce gender inequities without tailored specific policies.

Implications and Recommendations: The study's findings emphasise the need for comprehensive, gender-focused policies within economic recovery plans. Key recommendations which are guided by this dissertation include:

1. **Sector-Specific Financial Support**: Financial aid should target female-dominated sectors like healthcare, retail, and caregiving, which are more vulnerable to economic downturns.
2. **Gender-Sensitive Hiring Practices**: Economic recovery programs should incorporate equitable hiring practices, ensuring that both genders benefit equally from employment opportunities in post-crisis periods.
3. **Flexible Work Policies and Childcare Support**: Expanding flexible work arrangements and supporting childcare could enable more women to return to the workforce, particularly in caregiving-intensive sectors.

4. **Investment in Digital and Remote Work Infrastructure**: Developing countries should prioritise digital infrastructure to support remote work, which could benefit female-dominated sectors and reduce gender pay disparities in the long term.

These recommendations are crucial for policymakers to ensure that future economic growth is inclusive, addressing the structural disparities that exacerbate gender inequality during crises.

5.3 Confidence in Results, Validity and Generalisability

Data Source and Quality

The study utilised high-quality, reputable datasets such as Google Mobility Reports, Our World in Data, WHO COVID-19 statistics, and Statista's gender pay gap data. These sources are widely recognised for their thoroughness, global scope, and reliability in findings.

Handling of Missing Data

The study faced challenges with missing data, especially within the WHO and mobility datasets. Instead of using interpolation or imputation, which could introduce artificial trends, missing data was retained in its original form. This approach to handling missing values reinforces the data's integrity, ensuring that analyses reflect genuine patterns rather than statistical artefacts.

Study Rigour

The study employed a diverse and well-considered set of analytical techniques:

1. **Time-Series and Geospatial Analysis**: Smoothing techniques like the 7-day moving average were employed, and similar studies also employed them to reduce daily volatility and enhance trend clarity. The integration of geospatial visualisation further allowed for a broad understanding of regional mobility patterns, providing a detailed view of COVID-19's impact across countries and sectors.
2. **Clustering Analysis**: The use of K-means and hierarchical clustering, with validation through silhouette scores and the elbow method, provided reliable insights into grouping countries by mobility patterns. In terms of clustering analysis, the close positioning of clusters in the PCA results does not diminish the validity of the analysis. Rather, it highlights the complexity of mobility trends during the COVID-19 pandemic, suggesting that countries faced similar mobility challenges despite differences in policy or economic structure.

3. **Predictive Modeling**: The Prophet model, chosen for its adaptability to non-linear data and temporal fluctuations, proved effective in forecasting gender pay trends under different scenarios. Comparisons with linear regression using statistical measures also validated the choice to use Prophet.

Limitations and Potential Biases

Despite these strengths, certain limitations should be acknowledged. The reliance on Google Mobility Reports, which collect data only from individuals who enable location tracking on their devices, may introduce a selection bias. This limitation, though minimised by focusing on broad trends, means that the study's mobility patterns may be less representative of certain demographic groups, especially in low-income areas with limited smartphone access.

Additionally, while clustering and regression analyses provide valuable insights, they are limited in capturing causal relationships. The study's reliance on linear models, for example, may oversimplify complex socioeconomic interactions, particularly in forecasting long-term trends in gender pay disparity. Future research could address these limitations by incorporating non-linear models, causal inference methods, and more specified data, which could enhance precision and trend accuracy.

Another important limitation is the baseline period for measuring mobility changes, set between January and February 2020. This fixed baseline does not account for seasonal variation in movement patterns. As a result, some observed changes in mobility may reflect seasonal shifts rather than solely the impact of the pandemic, potentially influencing the interpretation of mobility recovery patterns. This was highlighted by (Mathieu et al., 2020).

Additionally, the study's use of annual unemployment data may not fully capture the real-time impact of the pandemic on the labour market. Annual averages do not capture the key time variations and provide an incomplete picture of disruptions faced by workers. For instance, individuals who retained employment but were not actively working, those who stopped job-seeking, or those working reduced hours are all counted as employed, potentially underestimating the true scale of economic hardship. To better reflect labour market shifts, future studies should consider using monthly or quarterly unemployment data. This issue was highlighted by the study of (Lee et al., 2020).

Conclusion on Confidence

Overall, the study's rigour, high-quality data sources, and approach to data handling ensure the reliability of this study's findings. While certain limitations are acknowledged, the study provides a comprehensive analysis of broad global trends in mobility, labour market impacts, and gender pay disparities during the COVID-19 pandemic. The results offer a well-supported foundation for understanding the socioeconomic effects of COVID-19 and present actionable insights for mitigating gender disparities in future crises.

6. Evaluation, Reflections and Conclusions

6.1 Evaluation of Project Work

This project aimed to assess the impact of COVID-19 on global mobility patterns, labour market outcomes, and gender pay disparities, with a focus on varying economic structures and policy responses across different regions. The objectives were ambitious but well-suited to current research needs, as understanding the long-term impacts of COVID-19 on the economy and gender inequality is crucial for future policy-making. Each objective was systematically addressed through methods such as clustering, correlation analysis, and predictive modelling, providing a comprehensive framework to evaluate mobility, economic resilience, and labour market disparities.

The selection of objectives and research questions allowed the study to build on existing literature while providing new insights into the factors influencing pandemic effects in various sectors. The use of reputable data sources, including Google Mobility Reports and Our World in Data, and cross-referencing to relevant studies supported the study's credibility. Clustering methods were particularly effective in capturing shared mobility trends across different economic structures, allowing for the analysis of general patterns while acknowledging country-specific contexts. The predictive analysis further helped estimate the trajectory of gender pay gaps, highlighting the need for targeted policies to close these disparities and how the pandemic impacts future labour market disparities.

The quality and scope of the results are down to the analytical methods and conclusions drawn directly from the findings. However, certain limitations were identified, such as the seasonal variability in mobility data, which could potentially affect the interpretation of pandemic-specific changes. Moreover, reliance on annual averages for unemployment data presented challenges in capturing real-time labour market disruptions. Addressing these limitations in future studies could refine the predictive accuracy and overall relevance of similar research.

6.2 Reflections on the Project Process

Reflecting on the project process, several valuable lessons emerged regarding data handling and method choices. Working with time-series data on global mobility trends and economic indicators emphasised the importance of thorough exploratory data analysis (EDA) and flexibility in adjusting methods based on preliminary findings. The clustering analysis, for instance, revealed patterns in shared mobility trends across countries, which later informed a more intricate understanding of the resilience factors within G20 and LDC contexts.

A notable limitation was the January-February 2020 baseline used in mobility data, which did not account for seasonal variations. This fixed baseline presented challenges in distinguishing between pandemic-driven and seasonally influenced changes in mobility. Recognising this limitation highlighted the need for seasonal adjustments in future studies to ensure that the data more accurately reflects COVID-19-specific impacts. Breaking down the study into specific time periods helped assess and compare mobility trends and economic impacts over different phases of the pandemic.

Additionally, the study's use of annual unemployment data may have oversimplified labour market disruptions, as annual averages do not fully capture rapid employment changes during a period of crisis. Future research would benefit from incorporating more frequent data points (e.g., monthly or quarterly) to better capture labour market dynamics. This experience emphasised the importance of data granularity, particularly when assessing gender-sensitive sectors.

The choice of K-means and hierarchical clustering methods was effective, but the study could have benefited from exploring more advanced clustering techniques, such as density-based clustering, to capture unique country-specific trends. Such methods could improve the analysis of mobility and resilience factors, providing a more detailed understanding of the varied challenges countries face. Alongside other machine learning and predictive models to predict the gender pay gap in the future. Although there was a comparison between prophet and linear regression, incorporating a wider array of models would enhance this analysis.

6.3 Conclusions and Implications

This study contributes to understanding COVID-19's varied impacts on global mobility, labour markets, and gender pay disparities, highlighting economic and policy factors that shape these outcomes. The findings offer several key insights:

1. **Mobility and Economic Resilience**: The study concludes that G20 and LDC countries exhibited different economic and mobility responses to COVID-19. In G20 nations, digital infrastructure and adaptable policies allowed for more resilient mobility patterns and economic recovery, while LDCs, with higher informal employment, relied on physical presence, making mobility essential for economic stability. The findings emphasise the need for economic policies that reflect each region's structural characteristics to balance economic needs with public health during crises.
2. **Labor Market Outcomes and Unemployment**: Mobility restrictions were closely tied to labour market outcomes, especially in female-dominated sectors where physical presence is often required. These findings highlight the vulnerability of sectors with limited remote work capacity, underscoring the importance of digital infrastructure and flexible work arrangements in reducing labour market disruptions.
3. **Gender Pay Gap Projections**: The predictive analysis suggests that without intervention, the gender pay gap is likely to persist or widen in the years following the pandemic. The findings emphasise the necessity for gender-sensitive recovery policies that directly address disparities in sectors hit hardest by COVID-19, particularly in LDCs where informal employment is prevalent. In general, the study found that focusing on increasing mobility and economic measures such as unemployment and GDP has shown a positive trajectory in addressing the gender pay gap.

Implications: The study highlights the importance of inclusive and gendered economic recovery strategies. Governments should consider flexible hiring practices, targeted financial support for vulnerable sectors, and investment in digital infrastructure to mitigate disparities. Expanding remote work and flexible policies in female-dominated sectors could help prevent the worsening of gender inequalities in future crises.

6.4 Recommendations for Future Work

Building on the findings and limitations identified, several recommendations are suggested to enhance future research:

1. **Incorporate Seasonal Adjustments in Mobility Data**: Future studies should consider seasonal variation by adjusting baseline mobility data. This would allow for a clearer interpretation of pandemic-specific trends, minimising the risk of seasonal fluctuations skewing results.

2. **Specific Unemployment Data**: Utilising monthly or quarterly unemployment data could provide more precise insights into the labour market impacts of mobility restrictions, allowing researchers to capture short-term fluctuations more effectively.
3. **Advanced Clustering Techniques**: To capture finer differences in country-specific resilience and response, future work could explore advanced clustering methods, such as density-based clustering or time-series clustering. These methods may offer more accurate insights into mobility patterns across varied economic contexts.
4. **Incorporate Comparative Insights from Related Studies**: Drawing from research on similar viral outbreaks, such as the study on Zika virus impacts (Ryu, 2020), could offer valuable context. The Zika study's examination of gendered labour market impacts and economic disruptions is particularly relevant for understanding COVID-19's effects on female employment and caregiving roles. By comparing COVID-19 with other outbreaks, future studies could better anticipate gender-specific vulnerabilities and resilience patterns.
5. **Integrate Policy and Economic Resilience Factors**: As shown in the study conducted by (Caselli et al., 2022), adaptable policy frameworks and groundwork for digital infrastructure play a crucial role in economic resilience. Future research could incorporate a policy analysis that examines how variations in labour regulations and economic policies contribute to different recovery and stability levels. This approach would deepen understanding of which policies most effectively support labour market stability during pandemics.

6.5 Personal Reflections and Lessons Learned

Conducting this study has provided significant learning in data science, data analysis and independent research. Working with large-scale datasets on mobility and economic indicators required a logical approach to data exploration and iterative refinement. The project highlighted the importance of understanding and addressing data limitations early in the process. For example, recognising the need for seasonal adjustments in baseline mobility data emphasised the importance of context-aware analysis, a lesson that will inform future work.

Handling complex clustering and predictive modelling also reinforced the need for critical assessment of methods. The use of K-means and hierarchical clustering revealed shared challenges among countries despite structural differences, underscoring that clustering should sometimes go beyond simple categorisations.

Choosing more tailored data sources, such as monthly unemployment metrics, would have offered clearer insights into labour disruptions. This was supported by findings from the study (Ryu, 2020), which suggested the need for precision in studies examining gendered impacts.

6.6 Conclusion

In conclusion, this study has provided insights into how COVID-19 affected mobility, labour markets, and the gender pay gap across a wide range of countries with different economies and policies. The findings highlight the need for policies that consider each country's specific context to support recovery and reduce gender inequality. This research adds to the understanding of pandemic impacts and offers a foundation for further study into how targeted policies can promote fair recovery across different sectors and regions.

Glossary

PHEIC: Public Health Emergency of International Concern, declared by the World Health Organization when a public health event poses a risk to multiple countries.

Labour Market: The supply of available workers in relation to available work.

Gender Pay Gap: The difference in average earnings between men and women.

Regression Analysis: A statistical method for examining the relationships between variables.

Geospatial Analysis: The use of geographic data to study and analyze phenomena and patterns.

Machine Learning: A type of artificial intelligence that enables computers to learn from data and make decisions.

Non-Pharmaceutical Interventions (NPIs): Measures such as social distancing and lockdowns that do not involve medications or vaccines are used to control the spread of disease.

Agglomerative Clustering: A type of hierarchical clustering that builds clusters by iteratively merging smaller clusters based on their similarities.

Choropleth Map: A type of thematic map in which areas are shaded or patterned in proportion to the value of a variable being represented.

Principal Component Analysis (PCA): A dimensionality reduction technique that transforms a large set of variables into a smaller one

Government Containment Health Index: A metric used to evaluate the stringency of government measures to contain health crises,

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Appendix A - Project Proposal

City university of London

Project Proposal for MSc in Data Science

Name: Sahan Chowdhury

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Project Title: "Mobility patterns of COVID 19 and the impact on the labour market specifically gender pay gap"

Supervisor: Natalia Andrienko

Introduction

Purpose of work

The Covid-19 Pandemic has undoubtably brough many unprecedented disruptions as well as benefits in various aspects of society, from redefining the way we work, interact, and navigate through our daily lives. This study focusses on the affect COVID-19 pandemic had on mobility patterns, and how this reverberated throughout the labour market and the affect it had on gender pay gap. Using various online datasets available regarding mobility patterns and labour market data specifically gender pay disparity over time amongst different regions. The study will employ a range of statistical, visual and machine learning techniques to analyse these effects comprehensively. There have been various studies conducted since the covid-19 epidemic, that have examined the immediate effects of the pandemic on employment and mobility. However, there is a lack of research on the long-term implications of these changes on gender pay disparity in a global context, and how mobility patterns influenced this. This research aims to fill the void by providing a detailed analysis of the pandemics impact on how altered mobility patterns influenced, job prospects, employment rates, and pay disparity between genders.

Motivation

In was reported in 2023 the uncontrolled gender pay gap in the world stood at 0.83, meaning that woman earned 0.83 dollars for every dollar earned by men (*Statista. (n.d.))*, an increase by 1 cent since COVID-19 began towards end of 2019. This highlights the constant challenge woman face in achieving pay parity with men for the same jobs, *figure (1)* obtained from *(Office for National Statistics, 2023),* shows a figure of the gender pay gap for full time and part-time. Between 2020 -2021 there seems to be a slight increase in the gap percentage. Although the graph overall depicts a steady decrease. The disruption COVID-19 has caused such as work from home schemes and digitalization causing the wage gap to further aggravate.

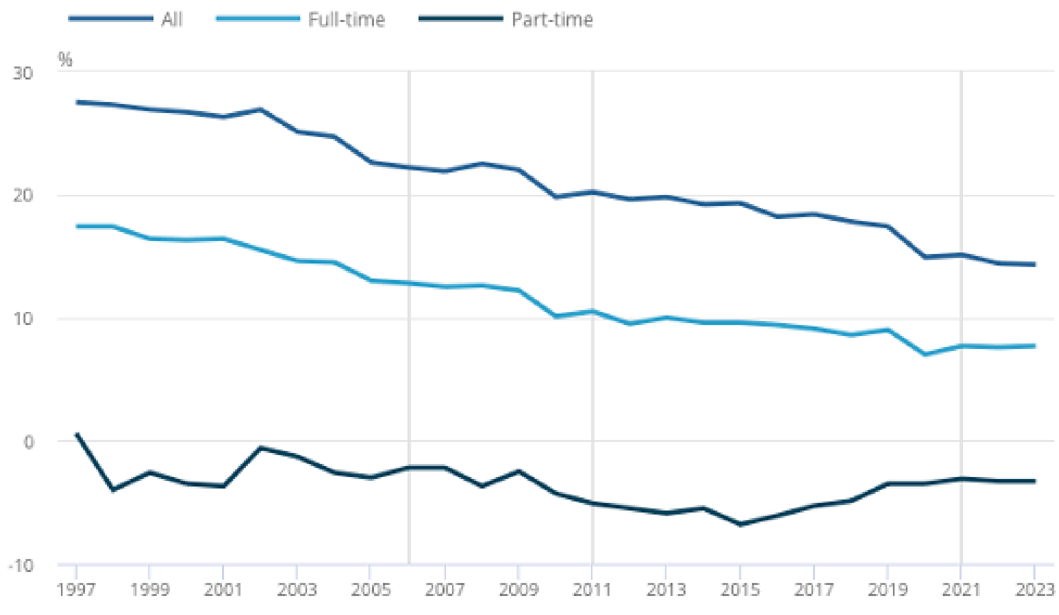

Figure (1) showing the gender pay gap for median gross hourly earnings, UK, 1997-2023 (Office for National Statistics, 2023)

Woman have historically faced difficulty in achieving pay parity, and COVID-19 has only further heightened these challenges. The lockdowns imposed by government across the world had a larger impact on the mobility of woman and younger cohorts *(Caselli, F., Grigoli, F.,* *Sandri, D. and Spilimbergo, A. (2021)).* Mobility patterns goes beyond mere restrictions imposed; it looks at the two-way relationship between pandemic developments and mobility trends of people in different regions. Mobility patterns are closely related to gender pay disparity, highlighting the multifaceted impact of the pandemic on labour market dynamics. As a study stated, 'impact of COVID-19 on mobility rates is greatest amongst women' (Mobycon. (n.d.)).

Overall aims and objectives.

The aim of this study is to understand how COVID-19 has affected the movement of people across the world and how this also affected job prospects and pay. The effect of mobility patterns will also be used to assess the extent to which it has affected employment opportunities and the gender pay disparity and identify solutions to address these challenges and promote equality in the labour market.

Aims:

- Investigate impact of COVID-19 on mobility patterns globally
- Examine how changes in mobility patterns have affected job prospects and current jobs.
- Examine how COVID-19 has affected the pay for different demographics.
- Assess relationship between mobility patterns and gender pay disparity.
- Evaluate the extent to which mobility patterns has influenced employment opportunities.
- Identify solutions to address the challenges arising from changes in mobility patterns and promote equality in the labour market.

Objectives

- Using datasets to compare changes in mobility patterns before, during and after COVID-19
- Determine impact of mobility patterns on job availability and pay.

- Statistical analysis and to explore relationship between mobility patterns and gender pay disparity.
- Create visual representations to reflect findings for easy interpretation.
- Clustering demographic groups based on mobility pattern and employment.
- Policy recommendations and interventions to mitigate gender pay disparity and promote inclusivity in the labour market.

Outcomes

- Gain insights of impact of COVID-19 on mobility patterns across the world.
- Gain insights in how changes in mobility patterns have influenced job prospects and employment (labour market) globally.
- Quantitative analysis revealing effect of COVID-19 on wages and income levels between demographics.
- Comprehensive results from statistical analysis giving insights between relationship of mobility patterns and gender pay disparity.
- Clustering analysis identifies key demographics.
- Evidence based policy recommendations and interventions aimed at mitigating gender pay disparity and promoting equality in labour market.

Beneficiaries

Although this research has no direct beneficiaries, several groups may find the findings valuable. Labour force, individuals and communities affected by changes in mobility pattern and labour markets, can benefit from understanding how these shifts have impacted job opportunities and income levels, enabling them to adapt to new employment trends and advocate for fairer labour practices. The level of detail within this analysis may also benefit businesses and industries affected by shifts in mobility may adapt their business models, making more informed decisions regarding remote work policies, workforce distribution and the structure of distributing pay. Academic researchers and scholars may also find this research valuable, and possibly contribute to the broader academic discourse of the socioeconomic impacts of COVID-19. Furthermore, insights gathered from this research may be used by governments and policy makers to formulate policies aimed at reducing gender pay disparity and promoting equality in the labour market.

Critical Context

Spatial temporal analysis of mobility patterns Covid 19

The study of *(Loisate et al., 2023*), explored the impact of COVID-19 pandemic on human mobility in Zambia, located in sub-Saharan Africa. This was done using mobile phone data and transmission models. It highlighted the importance of mobility data and looking at the changes from March 2020 to July 2021. It found that mobility decreased strict NPIs (non-pharmaceutical interventions) but returned to baseline levels despite subsequent waves. It was clear from this study initial pandemic responses had a greater impact on mobility that the latter. The study utilized spatial visualization and spatial clustering, which will be adopted for this research too understand how mobility behaviours and patterns evolved over the course of the pandemic. Just as the study of *(Loisate et al., 2023)* highlighted the significance of mobility data to discern societal responses to the pandemic, this research aims to display the importance of analysing mobility patterns in clarifying the broader socioeconomic impacts of Covid-19, to be specific regarding employment and gender pay disparity. Mobility data will be vital to make key findings, as it can provide disparities in movement patterns between genders. However, as a study stated there is a limited understanding of policy effectiveness from a spatiotemporal perspective. *(Li et al., 2021)*

Visual analytics approaches

Alongside spatiotemporal analysis, other visualization techniques will as be important to gain a comprehensive insight of the research. The study of *(www.iza.org, n.d.)* deployed a range of visualisation techniques and descriptive and bivariate statistics to showcase and analyse the impact of covid 19 public health policies on mobility with a focus on gender differences in a town in France. Exploratory data analysis and visualisations were used to identify factors influencing mobility behaviour and highlight aspects for further investigation. The research provided a comprehensive guide for policymakers and urban planners, during pandemic and post pandemic. Applying similar like visualisation techniques can enhance the quality of analysis and better understand the context of my study. An interesting find from this paper was that during lockdown woman made less trips than men 'women made 1.19 daily trips versus 1.46 for men.' *(www.iza.org, n.d.)*. However, post lockdown woman was predicted to make more trips on average per day than men. The study hasn't concluded as to the factors for this mobility behaviour, this gives a scope to further investigate the underlying factors driving these gender differences in mobility.

Regression Analysis in Gender Wage Gap Studies

A regression model was run to identify the causal factors for the change in Gender wage gap by the study conducted by LSE students [12]. This study aimed to explore the impact and causes for gender pay gap within the UK using publicly available dataset. The study implemented a regression analysis to assess different working environments hybrid and remote across different industries and use the findings to find the causes for the gender pay gap within the UK. The findings showed a decrease in the gender wage gap since covid first hit in the UK, with woman in the top income quartile contributing significantly to this. However, the study also highlights that labour market inequality for woman may persist longer than the pandemic. Regression analysis seemed to be a useful tool as it allowed to quantitatively assess the relationship between various factors, as for my research regression analysis can prove to a valuable tool as can assess a larger number of variables and mobility patterns affect gender pay.

Machine learning techniques for mobility prediction

The research conducted by *(Xu et al., 2023)* used a range of machine learning algorithms such as Random Forest, Support vector machines (SVM's), K nearest neighbours and Artificial neural network to model post pandemic travel preferences amongst residents in the state of Alabama. The study wanted to focus primarily on the change in individuals' attitudes towards shared mobility and active travel post pandemic. The study compared different algorithm to model post pandemic insights, and reveal relationship between demographic, commuting habits and post pandemic travel intentions. Incorporating machine learning techniques in my study this enables to model future mobility patterns and the effect on future gender pay, this can also enable to assess individuals' attitudes towards mobility and travel behaviour across the world. For instance, how changes in mobility patterns, such as increased reliance on remote work and reduced commuting trips, has affected job prospects and employment rates. Using a range of machine learning models enables to compare different modelling approaches to assess which model is most suited for this subject of matter.

Statistical analysis

The study of *(Bergman and Fishman, 2023)* provides a holistic overview of mobility reductions to control the spread of COVID-19. It analysed the temporal aspect between COVID 19 transmission rates and societal mobility levels using data sources from Google and Apple. The research applied reduced form regression estimates, correlation analysis and time series analysis to analyse the data and gain valuable insights. The research findings were that while mobility reduction generally lowered COVID-19 transmission rates, ultimately the effectiveness was dependant on regional context and temporal factors. For my research, statistical analysis will be essential to quantify the extent to which mobility patterns affect employment and gender pay disparity. It will also be vital for employing clustering analysis and regression analysis.

Research gap.

The critical context highlighted the use of techniques such as spatial-temporal analysis, visual analytics, regression analysis, and machine learning techniques to understand different aspects of mobility patterns and correlate this to gender wage gaps. It has laid the foundation to conducting this study and give a holistic understanding of COVID-19 mobility patterns and the effect on gender pay gap. This study not only contributes to academic discourse but also offers practical implications for addressing gender pay disparities in the wake of the COVID-19 pandemic.

Approaches: Methods & Tools for Design, Analysis & Evaluation

Literature review

Literature review is an essential step to gain understanding of existing research and build preliminary knowledge of the subject *(Western Sydney University, 2017).* Ongoing literature review would be conducted on various academic databases relating the topic.

Data collection

Datasets will be obtained, containing data from pre-pandemic, pandemic, and post pandemic periods covering all regions. The datasets that are currently obtained are from Eurostat *(ec.europa.eu, n.d.),* which contains data of gender pay gaps within Europe. As there is no singular dataset which contains all the data required, data will have to be gathered throughout the course of this research. Furthermore, Google mobility trends *(Our World in Data, n.d.)* contains mobility data, and the world bank *(World Bank Gender Data Portal, n.d.)* contains labour force participation rate which will also be useful, alongside this further data will be collected throughout the research process.

Data Pre-processing

Data will be processed and filtered accordingly. Missing values and duplicates will be handled with and ensured that there is consistency within the data. The ideal data should encompass pre-covid-19, during covid-19 and post covid-19. In addition, data will be scaled and standardised where required. The main variables that will be required is time, mobility patterns, geographic locations, employment rates, gender demographics and wage disparities, alongside any other variable such as occupation or sector will also be useful in this study. Moreover, since multiple data sources will be used, it is important pre-processing is done correctly to seamlessly integrate datasets where possible. Principal component analysis will be conducted where required, so that data dimensionality is reduced while preserving the key information, to enhance performance when used with machine learning algorithms.

Statistical analysis

Descriptive statistics will be used to summarise characteristics of the data, bivariate statistics such as covariance and correlation analysis will be conducted. Alongside this multiple regression analysis will be utilized to analyse the relationship of multiple predictors, such as mobility patterns on job availability and pay. From literature review it seemed logistic regression analysis was also commonly used, and this will also be considered.

Visual analytics

Visualisations such as scatter plots and choropleth maps will be used to provide intuitive representations. These visualisations will allow for identification of patterns, trends, and underlying findings. Time series visualisations will also be used to incorporate the time aspect to be able to make evidence-based comparisons.

Machine learning application

Machine learning algorithms, and predictive modelling will be utilised to understand the relationship between mobility patterns and labour market dynamics. Using an array of machine learning algorithms Random Forest, support vector machines (SVM's) and K-nearest neighbour. Comparisons can be made for the different algorithms and use for future prediction in mobility and wage gap disparity. Furthermore, clustering algorithm K-means and hierarchical will be applied to identify and partition demographic groups based on mobility patterns.

Evaluation

Evaluation of this study will look at 3 key components, robustness, reliability, and validity. Any assumptions made through the analysis will be clearly stated for clarity. The effectiveness of data collection and pre-processing techniques will be assessed based on completeness, consistency, and accuracy. Secondly statistical analyses conducted will be rigorously evaluated. The evaluation will involve scrutinizing the appropriateness of statistical methods used, the validity of assumptions made, and reliability of results obtained. Any findings that do not contribute meaningful insights or have limited application to the topic will be revaluated or discarded. As for machine learning models, a comprehensive evaluation measure will be performed. Metrics such as recall, precision and F1-score will be computed to quantify the model's performance. The use cross validation will be used alongside to improve reliability. Moreover, visual analytics approaches will be evaluated based on the effectiveness in conveying the underlying message and the information. The evaluation process will be an iterative process with continuous improvements. Through these carefully considered approaches of evaluation, this study aims to make a meaningful contribution to academic research of COVID-19 mobility patterns and the impact on the labour market specifically gender pay gap.

Ethics

Ethical considerations were a key aspect when conducting this proposal. After reviewing the City University ethics review form, there was no further action required. This study does not include any participants. Ethical principles remain integral throughout all stages of conducting this study, ensuring data privacy, confidentiality and integrity are upheld at every step of the research process.

Risks

Risk	Likelihood (1-3)	Consequence (1-5)	Impact (L x C)	Mitigation
Unable to find appropriate datasets	2	5	15	Create a robust data acquisition plan,

				going over multiple sources
Poor data quality	2	3	6	Ensure data is properly processed and if not use other data
Tasks taking longer than the guideline	1	2	2	Sticking to the workplan and leaving enough time in case of any unprecedented events
Topic becomes too broad by going off a tangent or misunderstanding	2	2	2	Stick to the topic research questions, and regular meetings with supervisor to stay on track
Software failure	1	4	5	Implement a backup for all work
Machine learning models either don't work or take too long	2	3	6	Conduct thorough testing and validation of machine learning models on smaller subsets of data
Data loss	1	5	5	Ensure all work is regularly backed up

Table (1): Showing table of potential risks breakdown.

Workplan

Category	Task	Start date	end date	Weeks											
				july				August				September			
				1	2	3	4	1	2	3	4	1	2	3	4
Project Proposal	Write proposal	10/05/2024	19/05/2024												
	Send proposal for review	16/05/2024													
	Submit Proposal	19/05/2024													
Supervisor Meeting	meeting 1	01/07/2024	05/07/2025												
Literature review	Literature reading and searching	01/07/2024	10/07/2024												
	Literature Review	05/07/2024	12/07/2024												
Obtain datsets	Data gathering, preprocessing & parsing in jupyter notebook	10/07/2024	17/07/2024												
	Explore initial insights from pre-processed datasets	10/07/2024	19/07/2024												
Supervisor meeting	Meeting 2	08/07/2024	10/07/2024												
Statistical Analysis	Begin exploratory data anlysis	15/07/2024	19/07/2024												
	Conduct statistical analysis (bivariatel, decriptive, time series)	19/07/2024	22/07/2024												
	Examine relationship and summarise findings	22/07/2024	24/07/2024												
Visual analytics	Visalisation creation	22/07/2024	28/07/2024												
Dataset reduction	Experiment with PCA	26/07/2024	28/07/2024												
Supervisor meeting	meeting 3	29/07/2024	31/07/2024												
Regression analysis	Multi regression analysis	01/08/2024	04/08/2024												
Machine learning	Machine learning model implementations	05/08/2024	11/08/2024												
	Clustering	12/08/2024	16/08/2024												
	Evaluate models	17/08/2024	18/08/2024												
Supervisor meeting	meeting 4	19/08/2024	23/08/2024												
Report	Additions	21/08/2024	25/08/2024												
	Report writing	01/08/2024	08/09/2024												
	Feeback from first draft	09/09/2024	13/09/2024												
Supervisor Meeting	meeting 5	16/09/2024	20/09/2024												
	Feedback of final draft + proofread	18/09/2024	22/09/2024												
	Submission	23/09/2024	27/09/2025												

Figure (2): showing project timeline and workplan.

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Research Ethics Review Form: BSc, MSc and MA Projects

Computer Science Research Ethics Committee (CSREC)

http://www.city.ac.uk/department-computer-science/research-ethics

Undergraduate and postgraduate students undertaking their final project in the Department of Computer Science are required to consider the ethics of their project work and to ensure that it complies with research ethics guidelines. In some cases, a project will need approval from an ethics committee before it can proceed. Usually, but not always, this will be because the student is involving other people ("participants") in the project.

In order to ensure that appropriate consideration is given to ethical issues, all students must complete this form and attach it to their project proposal document. There are two parts:

PART A: Ethics Checklist. All students must complete this part. The checklist identifies whether the project requires ethical approval and, if so, where to apply for approval.

PART B: Ethics Proportionate Review Form. Students who have answered "no" to all questions in A1, A2 and A3 and "yes" to question 4 in A4 in the ethics checklist must complete this part. The project supervisor has delegated authority to provide approval in such cases that are considered to involve MINIMAL risk. The approval may be ***provisional*** – *identifying the planned research as* likely to involve MINIMAL RISK. In such cases you must additionally seek ***full approval*** from the supervisor as the project progresses and details are established. ***Full approval*** must be acquired in writing, before beginning the planned research.

A.1 If you answer YES to any of the questions in this block, you must apply to an appropriate external ethics committee for approval and log this approval as an External Application through Research Ethics Online - https://ethics.city.ac.uk/		*Delete as appropriate*
1.1	Does your research require approval from the National Research Ethics Service (NRES)? *e.g. because you are recruiting current NHS patients or staff?* *If you are unsure try -* *https://www.hra.nhs.uk/approvals-amendments/what-approvals-do-i-need/*	**NO**
1.2	Will you recruit participants who fall under the auspices of the Mental Capacity Act?	**NO**

	Such research needs to be approved by an external ethics committee such as NRES or the Social Care Research Ethics Committee - http://www.scie.org.uk/research/ethics-committee/	
1.3	Will you recruit any participants who are currently under the auspices of the Criminal Justice System, for example, but not limited to, people on remand, prisoners and those on probation? *Such research needs to be authorised by the ethics approval system of the National Offender Management Service.*	**NO**
A.2 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee, you must apply for approval from the Senate Research Ethics Committee (SREC) through Research Ethics Online - https://ethics.city.ac.uk/		*Delete as appropriate*
2.1	Does your research involve participants who are unable to give informed consent? *For example, but not limited to, people who may have a degree of learning disability or mental health problem, that means they are unable to make an informed decision on their own behalf.*	**NO**
2.2	Is there a risk that your research might lead to disclosures from participants concerning their involvement in illegal activities?	**NO**
2.3	Is there a risk that obscene and or illegal material may need to be accessed for your research study (including online content and other material)?	**NO**
2.4	Does your project involve participants disclosing information about special category or sensitive subjects? *For example, but not limited to: racial or ethnic origin; political opinions; religious beliefs; trade union membership; physical or mental health; sexual life; criminal offences and proceedings*	**NO**
2.5	Does your research involve you travelling to another country outside of the UK, where the Foreign & Commonwealth Office has issued a travel warning that affects the area in which you will study? *Please check the latest guidance from the FCO - http://www.fco.gov.uk/en/*	**NO**

2.6	Does your research involve invasive or intrusive procedures? *These may include, but are not limited to, electrical stimulation, heat, cold or bruising.*	**NO**
2.7	Does your research involve animals?	**NO**
2.8	Does your research involve the administration of drugs, placebos or other substances to study participants?	**NO**
A.3 If you answer YES to any of the questions in this block, then unless you are applying to an external ethics committee or the SREC, you must apply for approval from the Computer Science Research Ethics Committee (CSREC) through Research Ethics Online - https://ethics.city.ac.uk/ **Depending on the level of risk associated with your application, it may be referred to the Senate Research Ethics Committee.**		*Delete as appropriate*
3.1	Does your research involve participants who are under the age of 18?	**NO**
3.2	Does your research involve adults who are vulnerable because of their social, psychological or medical circumstances (vulnerable adults)? *This includes adults with cognitive and / or learning disabilities, adults with physical disabilities and older people.*	**NO**
3.3	Are participants recruited because they are staff or students of City, University of London? *For example, students studying on a particular course or module.* *If yes, then approval is also required from the Head of Department or Programme Director.*	**NO**
3.4	Does your research involve intentional deception of participants?	**NO**
3.5	Does your research involve participants taking part without their informed consent?	**NO**
3.5	Is the risk posed to participants greater than that in normal working life?	**NO**
3.7	Is the risk posed to you, the researcher(s), greater than that in normal working life?	**NO**

A.4 If you answer YES to the following question and your answers to all other questions in sections A1, A2 and A3 are NO, then your project is deemed to be of MINIMAL RISK. **If this is the case, then you can apply for approval through your supervisor under PROPORTIONATE REVIEW. You do so by completing PART B of this form.** **If you have answered NO to all questions on this form, then your project does not require ethical approval. You should submit and retain this form as evidence of this.**		*Delete as appropriate*
4	Does your project involve human participants or their identifiable personal data? *For example, as interviewees, respondents to a survey or participants in testing.*	**NO**

Appendix B - Word count

Section	Word count
Introduction	4164
Context	2421
Methods	8471
Results	10032
Discussion	2414
Evaluations, Reflections and Conclusions	1401
Total	**28903**

Figure(A1): Table showing wordcount