Spatial Analysis of Motor Vehicle Theft in Riyadh, Saudi Arabia

By

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The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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I declare that the research for this publication was solely my own work and that I am the lead author. The contribution of the co-authors, Andrew Evans, Alison Heppenstall and Nick Malleson, was purely editorial and advisory.

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Abstract

Though motor vehicle theft (MVT) has been a major problem in Saudi Arabia (SA) for several decades, particularly in the capital Riyadh, few researchers have investigated this problem. Likewise, understanding the creation of the spatiotemporal patterns of MVT as a key element in tackling crime is also under-researched. This study aims to address this substantial research gap by utilising routine activity theory (RAT) and crime pattern theory (CPT). However, two issues need to be taken into consideration: that RAT and CPT will be applied outside their original context in the West and that few studies have utilised them to model MVT. As such, a contribution of this study is the evaluation of the applicability of these theories to both the Saudi context and MVT in general.

The empirical work of this study using RAT and CPT was designed to meet two objectives. First, exploratory spatial analysis techniques were used to determine whether MVTs tended to show high concentrations in certain neighbourhoods and at particular times of the day. Second, regression analysis methods were implemented to identify and predict the factors that contributed to these concentrations of MVTs.

The main findings suggest that, due to the substantial difference between contexts, the spatiotemporal patterns of MVT in Riyadh were somewhat different from those in the West. Due to the nature of MVT, the variables associated with RAT explained MVT well at certain times of the day but were insufficient during other periods; however, the variables associated with CPT were not able to explain MVT well at any time of the day.

The final chapter of the study addresses the implications for research and police practice. A significant implication of this study is that the explanatory variables varied in their effects on MVT throughout the day and across the areas studied. This allowed for the provision of recommendations for the Saudi police, such as giving priority to tackling MVT in certain areas that experience high MVTs at particular times.

Table of Contents

Acknowledgements..iii

Abstract..iv

Table of Contents…………………………………………………...v

List of Tables..ix

List of Figures……………………………………………………xi

List of Abbreviations..xii

Chapter 1 1

Introduction 1

1.1 Background of the Study 1

1.2 Aims and Objectives 3

1.3 Structure and Overview of the Thesis 4

Chapter 2 7

Spatial Analysis of Crime Patterns 7

2.1 Introduction 7

2.1.1 The Geography of Crime 8

2.2 Environmental Criminology 12

2.2.1 Routine Activity Theory (RAT) 14

2.2.2 Crime Pattern Theory (CPT)... 16

2.3 Spatial and Statistical Analysis Methods 18

2.3.1 Exploratory Spatial Analysis Methods 19

2.3.2 Modelling Crime... 22

2.3.3 General Limitations of Spatial Analysis Methods..................... 28

2.4 Chapter Summary.. 30

Chapter 3 32

Saudi Arabian Context 32

3.1 Introduction 32

3.2 Characteristics of Saudi Arabia 32

3.2.1 Socio-Demographics... 34

3.2.2 Legal Systems 36

3.2.3 Weekly Routines ... 37
3.2.4 Built Environment ... 40
3.3 Crime in Saudi Arabia ... 42
3.3.1 Crime Statistics in SA ... 44
3.3.2 Studies on the Geography of Crime in SA ... 45
3.3.3 Motor Vehicle Theft ... 48
3.3.4 MVT Studies in SA ... 51
3.3.5 Police Practice in SA ... 52
3.4 Chapter Summary ... 55
Chapter 4 ... 57
Motor Vehicle Theft and Environmental Criminology Theory ... 57
4.1 Introduction ... 57
4.2 Existing MVT Studies in Western Countries ... 58
4.2.1 Routine Activity Theory ... 58
4.2.2 Crime Pattern Theory ... 65
4.3 How Might Differences Between Two Environments Influence the Applicability of Routine Activity and Crime Pattern Theories? ... 68
4.3.1 Routine Activity Theory ... 68
4.3.2 Crime Pattern Theory ... 72
4.4 Chapter Summary ... 74
Chapter 5 ... 76
Data and Methodology ... 76
5.1 Introduction ... 76
5.2 Data Description ... 77
5.2.1 MVT Dataset ... 77
5.2.2 Socioeconomic and Demographic Data ... 78
5.2.3 Environmental Features ... 79
5.3 Data Preparation ... 79
5.3.1 Boundaries of the Studied Area ... 79
5.3.2 MVT Measures ... 80
5.3.3 Census Data ... 82
5.4 Methodology ... 93
5.4.1 Exploratory Spatial Analysis Methods ... 95
5.4.2 Regression Analysis ... 97
5.5 Chapter Summary ... 118

Chapter 6 .... **121**

Exploratory Analysis of Spatial-Temporal MVT Patterns **121**

6.1 Introduction 121

6.2 Spatial Distribution of MVT Rates in Riyadh 121

6.3 Are these Spatial Patterns of MVTs Statistically Different? 124

6.4 Summary of Chapter 6 129

Chapter 7 .... **130**

Modelling MVT **130**

7.1 Introduction 130

7.2 MVT and RAT 131

7.2.1 Results of the OLS Regression Model 131

7.2.2 Results of the ML Regression Model 138

7.2.3 Summary 140

7.3 MVT and CPT 141

7.3.1 Result of the OLS Regression Model 141

7.3.2 Results of the ML Regression Model 146

7.3.3 Summary 148

7.4 Integration of the RAT and CPT Models 148

7.4.1 Results of the OLS Regression Model 148

7.4.2 Results of the GWR 152

7.4.3 Results of the ML Regression Model 162

7.4.4 Summary of the Integrated Model 164

7.5 Summary of Chapter 7 165

Chapter 8 .... **167**

Discussion and Findings **167**

8.1 Introduction 167

8.2 MVT and RAT 167

8.2.1 Motivated Offenders 168

8.2.2 Suitable Targets 172

8.2.3 Absence of Capable Guardians 173

8.2.4 Evaluating the Applicability of RAT 176

8.3 MVT and CPT 180

8.3.1 MVT Generators 180

8.3.2 MVT Attractors 183

8.3.3 Paths and Nodes 184

8.3.4 Evaluating the Applicability of CPT 186
8.4 Integrating RAT and CPT 187
8.5 Summary of the Chapter.. 188
Chapter 9 192
Conclusion and Policy Recommendations 192
9.1 Introduction 192
9.2 Summary of the Study Findings.. 192
9.3 Policy Recommendations 202
9.4 Research Limitations and Future Work... 204
9.5 Concluding Remarks 206
List of References ……………………………………………………………..207
Appendix A ………………………………………..…………………….226

List of Tables

Table 3-1: Saudi studies on the geography of crime 47
Table 5-1: Mean, median and standard deviations of MVT incidents in Riyadh 81
Table 5-2: Descriptive statistics of the RAT variables 89
Table 5-3: Descriptive statistics for the CPT variables 92
Table 5-4: Descriptive statistics for the MVT rates in the four time periods 99
Table 5-5: Descriptive statistics for the log of MVT rates 99
Table 5-6: The correlation matrix for all independent variables 103
Table 5-7: Total variance explained by the RAT components 104
Table 5-8: Total variance explained by the CPT components 105
Table 5-9: Total variance explained by the components for the integrated theories 105
Table 5-10: Rotated component matrix for the RAT components 107
Table 5-11: Rotated component matrix for the CPT components 108
Table 5-12: Rotated component matrix for the integrated theories components. .. 109
Table 5-13: Studentised residuals for RAT model 116
Table 5-14: Studentised residuals for CPT model 116
Table 5-15: Studentised residuals for the integrated model 117
Table 6-1: Spatial point pattern test output, S-Indices, MVTs in Riyadh 124
Table 7-1: Estimated coefficients for variables in the OLS regression models 132
Table 7-2: Correlation matrix for the RAT variables and MVT rates 134
Table 7-3: Estimated coefficients for PC Scores in the OLS regression models... 135
Table 7-4: Correlation matrix for the PCs with MVT rates 137
Table 7-5: Global Moran's I for the regression residuals 138
Table 7-6: Parameter estimates in the ML regression model 139
Table 7-7: Coefficients for the CPT variables in OLS regression models 142
Table 7-8: Correlation matrix for the CPT variables with MVT rates 143
Table 7-9: Estimated coefficients for PC scores in OLS regression models 144
Table 7-10: Correlations between MVT rates and the PCs 145
Table 7-11: Global Moran's I for the regression residuals 146
Table 7-12. Estimated coefficients in the ML regression model 147
Table 7-13: Estimated coefficients in OLS regression integration models 149
Table 7-14: Correlation matrix for the components representing the integrated theories 150

Table 7-15: Global Moran's I for the regression residuals **.................................... 151**

Table 7-16: Fitting information of the GWR models**.. 153**

Table 7-17: Global Moran's I for the regression residuals from GWR models**..... 153**

Table 7-18: Estimated coefficients in the ML regression model **........................... 163**

Table 9-1: Types of areas that are more vulnerable to MVT in certain neighbourhoods and at particular periods of time of the day**......................... 203**

List of Figures

Figure 2-1: Showing a summary of the process of formulating RAT **16**

Figure 3-1: A map showing Saudi Arabia and the capital –Riyadh City................ **33**

Figure 3-2: A population pyramid for Saudi population in 2007 .... **34**

Figure 3-3: A population pyramid for non- Saudi population in 2007 .... **35**

Figure 3-4: A bar chart showing the percentage of vehicle traffic for the working day on a normal day and during Ramadan in Riyadh. **38**

Figure 3-5: Hourly traffic volumes on Bronx-Whitestone Bridge, New York in the US in 2010.. .... **39**

Figure 3-6: Daily car traffic trends on all roads in the UK **39**

Figure 3-7: A street view of a residential area in Riyadh **40**

Figure 3-8: Street view shows houses and parked cars, Riyadh, SA **41**

Figure 3-9: Shops, grocery stores, restaurants and offices distributed along the street of a residential area in Riyadh **41**

Figure 3-10: The percentages of properties crimes in Riyadh, 1430H to 1434H(≈2009 to 2013).. **50**

Figure 5-1: Boundaries of the study area (Riyadh city) and Riyadh region **80**

Figure 5-2: Flow chart summarises the process of the methods applied in this study **94**

Figure 5-3: Spatial distribution of the PCA scores across the study area, Riyadh **113**

Figure 6-1: Spatial distribution for overall MVT rates in Riyadh, 2012 to 2014 **122**

Figure 6-2: Maps illustrating MVT rates throughout the four study periods in Riyadh from 2012 to 2014. .... **123**

Figure 6-3: Significant differences in MVT incidents between Period One and the other time periods **126**

Figure 6-4: Significant differences between MVT incidents between Period Two and Periods Three and Four. **127**

Figure 6-5: Significant differences between MVT incidents that occurred during Period Three and Four **128**

Figure 7-1: OLS regression residuals during Period Four **152**

Figure 7-2: Variations in the models' performances throughout the day and across the study area, Riyadh **156**

Figure 7-3: Effects of PC5 on MVT rates during Periods One and Two and across the study area, Riyadh **158**

Figure 7-4: Effects of PC1 on MVT rates throughout the day and across the study area, Riyadh. **160**

Figure 7-5: Effects of PC4 on MVT rates throughout the day and across the study area, Riyadh **162**

Abbreviations

MVT	Motor Vehicle Theft
SA	Saudi Arabia
UK	United Kingdom
US	United States
RAT	Routine Activity Theory
CPT	Crime Pattern Theory
OLS	Ordinary Least Squares
ML	Multinomial Logistic
GWR	Geographically Weighted Regression
HCDR	High Commission of the Development for Riyadh
MAUP	Modifiable Area Unit Problem
CPS	Calls for Police Services
NIC	National Information Centre
CIA	Central Intelligence Agency
LNEQ	Low or no Education Qualifications
HNV	Households with no Vehicles
SPSS	Statistical Package for Social Science
GIS	Geographic Information Systems
PCA	Principle Component Analysis
KMO	Kaiser-Meyer-Olkin
MSA	Measure of Sampling Adequacy
PC	Principle Component
AIC	Akaike Information criterion

Chapter 1

Introduction

1.1 Background of the Study

Motor vehicle theft (MVT) is a global phenomenon (Harrendorf et al., 2010). MVT rates vary by country due to a wide range of factors—cultural, social, demographic, physical and legal— each of which are unique to each spatial location. In most Western countries, MVT has typically accounted for fewer property crimes than other more dominant types of crimes. For example, in the US in 2015, larceny-theft accounted for 71.4% of property crimes, followed by burglary (20%), with MVT making up about 9% of property crimes (FBI, 2016). Meanwhile, in England and Wales, criminal damage accounted for the largest component of property crime in 2010, at about 24%, with burglary accounting for nearly 18% and MVT only 3.7% (Office for National Statistics, 2012). In Canada, in 2006, theft amounting to $5000 or below accounted for 52% of property crimes, whereas MVT accounted for 13.6% and burglary 21.4% (Silver, 2007).

Lower MVT rates in Western countries, such as the UK, the US, Canada and European nations, have been attributed to prevention efforts, such as improved vehicle security systems (Morgan et al., 2016) and other increasingly sophisticated security devices (Farrell et al., 2011a; Webb, 1994; Brantingham, P.J. and Brantingham, 1993). These lower MVT rates can explain why few Western-focused studies have been conducted on this type of crime compared to other major crimes. This lack of research on MVT has been noted (Suresh and Tewksbury, 2013; Lockwood, 2012; Walsh and Taylor, 2007a; Fleming et al., 1994), particularly in the area of analysing the spatial patterns of MVT (Piza et al., 2016; Lu, 2006).

In striking contrast, MVT has made up a significant share of property crimes in Saudi Arabia (SA) for several decades: accounting for 24.7% of all property crimes from 1985 to 1990 (1406 to 1411H under the Islamic Hijri calendar) (Alwelaie, 1993), and rising dramatically to 31% by 1435 H (≈ 2014) (Ministry of Interior, 2015). In 2015, despite the reduction in most property crimes, MVT increased to account for

34% of property crimes by 1436 H (≈2015), followed by burglary, which made up only 10.9% (Ministry of Interior, 2016). In Riyadh, SA's capital city, MVT accounted for 48.2% of all property crimes between 2009 and 2013 (Police Department in Riyadh, 2014). MVT, therefore, is a major concern for the public and authorities due to its impacts on the economy, society and individuals, and a MVT prevention strategy is an imperative need. The Saudi government has made efforts to tackle the problem of MVT, such as requiring imported vehicles to have immobilizer devices and anti-theft warning systems since 2001 (Public Security, 2016). Despite these efforts, especially by police forces, MVT remains a major problem in SA. MVT in SA rose from 2014 to 2015, with the capital Riyadh seeing the highest rate amongst Saudi cities (Ministry of Interior, 2016).

Despite the clear evidence that SA faces a MVT problem, few researchers have attempted to tease out the causality, focusing instead on the factors that lead to delinquency (Al-Qahtani, 2008; Al Angari, 2002; Al-Otaibi, 2002; Al-Shaheen, 1996). This lack of research on the patterns and causes of crime is not limited to MVT; few studies have analysed the occurrence of crime from a geographical perspective, and most existing research has been limited by weak theoretical formulations, poor data and inadequate analysis methods (Almatrafi, 2005; Mahya, 2003; Aldawsari, 1997; Al-Khalifah, 1997; Alwelaie, 1993; AlMarzougi et al., 1986). A significant under-researched area that could improve approaches to MVT in SA is understanding the concentration of MVTs at particular places and times. This focus is the key concept of environmental criminology (Wortley and Mazerolle, 2008). Environmental criminology primarily aims to "*prevent crime*" (Wortley and Mazerolle, 2008,p.2). Many crime prevention strategies have been designed based on crime analysis research built, in turn, on existing environmental criminology theories (Paynich and Hill, 2011). The most popular environmental criminology theories are routine activity theory (RAT) and crime pattern theory (CPT), which have been found to explain crime clustering over space and time well (Felson and Clarke, 1998).

Two issues, however, are expected when applying RAT and CPT to explain the problem of MVT in SA. First, these theories were constructed in research performed in Western countries. For example, RAT was based on work in the US (Cohen and Felson, 1979) and developed by Felson (1986), and CPT on work in Canada (Brantingham, P.J. and Brantingham, 1993). Both theories were proposed and developed within Western contexts with their own cultural, social, demographic and environmental factors that could affect criminals' and victims' behaviours in ways substantially different from the Saudi context. Secondly, the empirical research related to RAT and CPT mostly focused on burglary and robbery in the US and Canada, and MVT received little consideration when these theories were first conceived. Consideration of these unique issues is of paramount importance when applying these theories to understand MVT in SA, particularly in the capital city Riyadh.

This study will contribute significantly to knowledge. First, it will fill the substantial research gap in understanding the spatial and temporal patterns of MVT in SA, which will add to the body of knowledge on the geography of crime in SA. Furthermore, this study will apply RAT and CPT to a very different cultural context (SA), which will thus provide an evaluation of how applicable a Western-derived theory is to SA. Finally, the study will contribute to knowledge of to what extent environmental criminology theories can explain MVT.

1.2 Aims and Objectives

The central aim of this research is to understand the spatial and temporal patterns of MVT in SA, particularly in Riyadh, by applying routine activity theory (RAT) and crime pattern theory (CPT). To achieve this aim, the following objectives are proposed:

1. To review environmental criminology theories and spatial analysis techniques to better understand the theory of how spatial crime patterns are generated.
2. To compare the Saudi and Western contexts to identify any differences that could challenge the applicability of environmental criminology theories to the spatial analysis of MVT in Riyadh.
3. To critically review the crime literature on MVT in SA and policing efforts to tackle MVT in order to identify how this thesis can contribute to the existing body of knowledge about crime, particularly MVT.
4. To critically review Western MVT studies contextualised within the frameworks of environmental criminology theories to identify influential factors on MVT that should be examined in the analysis of MVT in Riyadh.
5. To explore the spatial patterns of MVT and detect significant differences in MVT across the study area and throughout the day in order to examine the first

theme of RAT and CPT, which suggests that crime concentrates at certain places and during particular periods of the day.

6. To predict and examine the relationship between MVT during four time periods throughout the day and a wide range of variables derived from RAT and CPT (and the integration of theories) that contribute to MVT concentration at certain places during particular time periods.
7. To evaluate the applicability of the concepts of RAT and CPT outside their original contexts.
8. To provide recommendations to improve Saudi police practices to tackle MVT.

1.3 Structure and Overview of the Thesis

This thesis consists of nine chapters and an appendix. The sequence of the chapters indicates the progression in accomplishing the research objectives outlined in the preceding section. In the following paragraphs, each chapter is described according to the research objectives.

Chapter 2 provides an understanding of the spatial dimension of crime, particularly its theoretical background, and explains the premises of the theories applied in this study (RAT and CPT). The process of spatial analysis of crime, conducted later in this study, is discussed. This chapter highlights the most popular spatial and statistical techniques applied in criminology, detailing their steps and assessing their uses and main limitations. Chapter 2 provides a foundation to understand the theory and methodologies used in this study and justifies the choice of theories, techniques and implications of the spatial analysis of MVT in Riyadh, addressing the first research objective.

After reviewing the context of the development of RAT and CPT in Chapter 2, Chapter 3 presents an overview of SA. Several characteristics of the Saudi context are described, and differences from the Western context are noted. Chapter 3 also provides the background to the MVT problem in SA and contrasts it to Western crime statistics. Before the review of empirical MVT studies in Western settings presented in Chapter 4, Chapter 3 ends with a critical review of existing crime and MVT research in SA. Finally, the Saudi police practices to address the problem of MVT are described, with the aim to understand the current situation in SA, particularly the social, cultural, physical, legal circumstances, crime rates and literature.

Chapter 4 is the last chapter presenting the theoretical framework of this thesis. First, MVT research using environmental criminology approaches in Western countries is critiqued. Next, the applicability of environmental criminology theories to the Saudi context is evaluated, taking into account the findings of earlier MVT studies and the contextual differences presented in Chapter 3. Chapter 4 provides information important to selecting the variables to represent the elements of RAT and CPT examined in this study.

Chapter 5 first describes the data used in the analysis, particularly each type of data used and how it was derived from the themes of RAT and the CPT. Then, the purpose of the techniques used in this study and how they were adapted to analyse the described data according to the study aims and objectives are explained in detail.

The results from applying these methods are presented in Chapters 6 and 7. Chapter 6 analyses the problem of MVT in Riyadh in terms of occurrences over space and time. This is considered to be a first step in understanding the spatial patterns of MVT in Riyadh through RAT and CPT. The spatial patterns of MVT incidents in Riyadh are visualised, and then the significant differences in MVT occurrence throughout the day are determined.

After the problem of MVT, particularly when and where it tends to occur most often, is described, Chapter 7 examines the question of why it occurs. The influences of various socioeconomic, demographic and physical factors on MVT are examined using the theoretical framework of RAT and CPT. Ordinary least squares (OLS) regression models are applied to explain MVT rates based on the selected variables representing RAT, CPT and an integration of these two theories. Following this, a multinomial logistic (ML) regression model is run to predict the probability of MVT occurrences during four time periods under RAT and CPT. Finally, geographically weighted regression (GWR) for modelling MVT rates at the four time periods is performed utilising the integration of both theories.

In chapter 8, the significance of the findings from the analysis is interpreted and discussed within the theoretical framework of RA and CPT and in relation to the literature review. This chapter highlights significant and novel findings regarding MVT in general and the extent to which the chosen theories can help to understand the MVT problem in SA.

Chapter 9 presents the conclusions drawn from the thesis. First, the main points of the research that describe how this thesis was done to achieve its aim are summarised. The chapter also provides a summary of the key findings of the study, including recommendations for policy. Following this, the chapter outlines the study's limitations and suggestions for future research, and it provides concluding remarks about this thesis. Finally, an appendix provides extra clarification of the outputs of the regression models run in the thesis.

Chapter 2

Spatial Analysis of Crime Patterns

2.1 Introduction

A fundamental aim of this research is to understand the underlying processes that drive the spatial patterns of MVT in Riyadh, SA. It is therefore essential to grasp the key theoretical concepts in the spatial analysis of crime, geography of crime and existing theories in order to develop the theoretical framework of this study. Understanding the spatial patterns of crime requires a thorough comprehension of the process of spatial analysis of crime. This chapter is divided into three main sections to accomplish these goals.

First, Section 2.1.1 discusses how crime events occurring at specific places at certain times generate spatial patterns and the reasons why the spatial and temporal dimensions are important for understanding crime. Then, the chapter introduces the principal themes of the environmental criminology theories (RAT and CPT) helpful in explaining why incidents of crime tend to cluster at certain spaces and particular times in Section 2.2.

After this explanation of the theoretical understanding of spatial crime patterns, Section 2.3 presents a review of the spatial analysis methods widely used to reach the understanding explained in Section 2.2. The first review is for methods that help to answer a key question about the spatial-temporal patterns of crime: Do spatial crime patterns vary throughout the day as a result of changes in daily activities? This question is answered through exploratory spatial analysis of crime data (Section 2.3.1). Section 2.3.2 describes the spatial and statistical methods used to determine why crimes tend to occur in certain neighbourhoods and during certain time periods of the day in order to understand and predict the spatial patterns of crime. In addition, Section 2.3.3 of Chapter 2 concludes by highlighting the key limitations of using spatial data in crime analysis. Section 2.4 provides a summary of the main discussion of Chapter 2.

2.1.1 The Geography of Crime

This research is carried out to study MVT at the neighbourhood level of Riyadh from a geographical perspective, so the geography of crime is at the heart of the theories and methods applied in this study. This section attempts to provide an introduction for this research and to provide a brief history of the evolution of the discipline. It then shows how the geography of crime has been developed, introducing the perspective of environmental criminology theories that are applied in this study (Section 2.2).

A brief Historical Development of the Geography of Crime

The analysis of crime has a long history with some of the earliest work being recorded in the early 19th century (White, M.D., 2007; Boba, 2005). It aims to understand why crime occurs in order to predict it, as this will enable decision makers and police officers to address plans for tackling crime (Boba, 2005; Canter, 2000). A range of different scientific communities have studied crime, for instance biologists, criminologists, economicists, psychologists, anthropologists and sociologists (Jeffery, 1959) and geographers (Lowman, 1986) each contributing new ideas and methods. Traditionally, studies adapted in the crime analysis field concentrate on identifying factors that contribute to causing crime. These factors are mainly related to criminal behaviour and societies (Jeffery, 1959). The geography of crime was ignored by most analysts until the first attempts made by the works of Guerry (1833) and Quetelet (1842), who examined the spatial distribution of crime patterns in France using maps (Eck and Weisburd, 1995). At the beginning of the twentieth century, a number of social scientists in the Chicago school carried out research on the geography of crime (Shaw and McKay, 1942; Shaw et al., 1929). This continued into the mid 1960s with researchers concentrating on exploring variations in crime using census data with other variables conducted under traditional statistical methods, such as regression techniques (Eberts and Sehwirian, 1968; Boggs, 1965; Fleisher, 1963).

Around the early 1970s, Jeffery (1971) and Newman (1972) conducted research that revealed an important finding suggesting that a built-up environment can contribute to reducing opportunities for crime. Jeffry’s work indicated that the structure of a built-up environment can affect the behaviour of offenders and thus affect crime opportunities. Meanwhile, Newman (1972) suggested that houses designed in such a way that allows occupants to observe their surroundings, such as through windows, can protect houses from potential offenders. Jeffery (1971) and Newman (1972) introduced the environmental criminology concept (Wortley and Mazerolle, 2008). Since then, geographical research into crime has unified with environmental criminology in developing theories for analysing spatial patterns of crime (Lowman, 1986; Block, 1979). Environmental criminology will be discussed in more detail in Section 2.2.

Why is the Geography of Crime Important in Crime Analysis?

Crime events are not evenly distributed in space and time, their occurrence is dependent on a number of related factors that are unique to each event (Anselin et al., 2008; Brantingham, P.J. and Brantingham, 2008). Crime incidents that are concentrated heavily in one or more places are defined as 'hot spots' (Eck et al., 2005). A hotspot can be explained as a location that contains a high number of crime events or rates in comparison to other places that have "average crime"(Chainey and Ratcliffe, 2005). Furthermore, the concentration of crime in a small number of neighbourhoods over a long period of time can suggest those neighbourhoods which are more susceptible to opportunities for crimes, whereas other neighbourhoods may not facilitate crime occurrences (Eck et al., 2000). For example, abundant research on MVT has found that it tends to show a higher frequency at certain places (Suresh and Tewksbury, 2013; Fujita, 2010; McCormick et al., 2007; Weisel et al., 2006; Lu, 2006; Rengert, 1997; Fleming et al., 1994; Harlow, 1988).

This high concentration of crime in specific neighbourhoods and blocks suggests that there may repeat victims and repeat offenders within these locations. Sherman et al. (1989), indicate that few places (nearly 3%) in the city accounted for the large proportion of crime (about 50%) in the city, indicating high repeat victimization in these areas. For example, Spelman (1995), analysed calls for emergency services in Boston (US) and found that the areas characterized as hot spots were about 10% of the total of the study area which made up approximately 50% of the sum of calls. This suggests that people with certain characteristics in certain places are more vulnerable to becoming victims of crime than other groups of people. Concentration of crime is not only in certain places, but also at certain times in those places (Sherman and Weisburd, 1995). This is evident in the case of MVT, as the majority of incidents occur on driveways near owners' houses at night (McCormick et al., 2007; Weisel et al., 2006; Mirrlees-Black et al., 1996; Clarke, R.V. and Mayhew, 1994; Fleming et al., 1994).

Identification of areas with high crime rates is considered a first step to understanding why specific neighbourhoods suffer from occurrences of crime (Chainey and Ratcliffe, 2005). Chronic crime locations can be influenced by characteristics of an area's features and more investigation may be required to explore the relationships between characteristics of places and crime. Anselin et al. (2000) point out that there is an association between areas with high crime rates and specific characteristics of people and types of land use. Previous crime studies found an association between crime occurrences and areas with certain characteristics, such as specific types of land use or socioeconomic and demographic variables (Chang, 2011; Eck and Weisburd, 1995; Greenberg and Rohe, 1984; Roncek, 1981). Hence, when areas with high concentrations of crime are detected, analysts can examine factors that might contribute to the continuing and increasing crime rates in these areas (Anselin et al., 2008). However, since each crime differs according to the nature of the offence (Cornish and Clarke, 2008), crime also differs according to the characteristics of the place in which it occurs. Consequently, there are variations in the spatial distribution of these patterns for each type of crime and thus spatial relationships are different for each type of crime (Eck et al., 2005).

Incidents of certain types of crime tend to show a high frequency of occurrence at particular times at certain places compared to other types of crime. For example, burglary occurs most often during daytime hours (Filbert, 2008; Grabosky, 1995; Hakim and Gaffney, 1995), whereas MVT tends to be most frequent during the night (Flowers, 2006b; Weisel et al., 2006; Clarke, R.V., 2002; Henry and Bryan, 2000; Mirrlees-Black et al., 1996; Fleming et al., 1994). Each type of crime differs in its spatial-temporal patterns due to the fact that patterns of crime opportunities vary from one crime to another (Felson and Clarke, 1998). Hence, there are different and various behaviour settings for different types of crime (Clarke, R.V., 1997; Brantingham, P.J. and Brantingham, 1993). The spatial analysis of crime patterns that aggregates into types, such as violent and property, leads to the misinterpretation of the crime phenomenon in the study area (Eck et al., 2005). Therefore, distinguishing between spatial patterns of different crime types is a critical step in crime analysis for adapting a suitable theory and spatial method that can reveal the underlying process creating these patterns, which could help to set effective preventative measures.

Nevertheless, there is no single factor that can be defined as the main cause for each type of crime. Crime can occur as a result of a combination of different factors coming together (Brantingham, P.L. and Brantingham, 1993b). The interaction between these influencing factors can make the determination of real causes of crime incidents more complicated. There is a strong interaction and association between the geography of crime events and the surrounding factors of location, such as demographic characteristics and physical design of the area (Eck and Weisburd, 1995). The presence of one or more contributing factor might lead to a concentration of crime incidents in certain locations, indicating spatial relationships between crime events and these factors (Roncek, 1981). It is a significant point to indicate here that the degree of influence of these factors on the occurrence of crime varies from one type of crime to another (Eck et al., 2005). Likewise, the degree of influence of these factors varies for the same crime type over space and time. This makes the process of understanding creation/causation of spatial patterns of crime more complicated and requires theories to structure ideas around.

Spatial Theories of Crime

In the early era of the analysis of crime, many theories were proposed to explain, describe and underline the process of crime occurrence. These theories tried to identify the causes of crime and link the factors surrounding the crime event to the crime itself. Crime theories can be divided into two fundamental types, based on their explanations of crime: the first tend to focus on how social factors, and life courses promote delinquency of the person who then becomes a criminal (Boba, 2005). They attempt to investigate the historical side of potential criminals, which is called traditional criminology theories (Wortley and Mazerolle, 2008). These are in contrast to the second category of theories that are concerned with explaining patterns of crime based on environmental variables, and are known as environmental criminological theories (Wortley and Mazerolle, 2008).

A major concern of traditional criminological theories is the social and economic factors that contribute to delinquency, and examining and developing theories from this viewpoint (Wortley and Mazerolle, 2008; Boba, 2005). Thus, traditional criminology theories emphasize the role of factors such as education, upbringing, employment opportunities and poverty, with delinquency. One of the traditional theories that gives attention to the spatial dimension of crime is social disorganization, which seeks to explore the influence of the characteristics of neighbourhoods on crime levels within these areas over a period of time (Andresen, 2010; Andresen, 2006b; Boggs, 1965). This theory was proposed by Shaw and McKay

(1942) who pointed out that those areas with high social disorganization containing high levels of poverty and population heterogeneity show an increase in delinquency levels. The theory came from observing that the level of delinquency was stable within specific areas over time (Shaw and McKay, 1942).

However, the offender is only one aspect of crime. Other crucial aspects of crime, such as the victim, geographical location and time, should be taken into account to gain a better understanding. Thus, it is not inevitable that crime will occur if the factors that lead to delinquency cannot be prevented. This is because people are not equally vulnerable to becoming victims of crime (Barkan and Bryjak, 2011). Some people have particular demographic characteristics that make them more susceptible to becoming victims of specific crimes (Barkan and Bryjak, 2011). Furthermore, time is an important aspect because crime frequency tends to vary over time (Felson and Poulsen, 2003; Van Koppen and Jansen, 1999; Sherman and Weisburd, 1995).

Variations in crime occurrence throughout time and space are caused by a wide range of socioeconomic, demographic and environmental factors (Chainey and Ratcliffe, 2005). Therefore, a combination of these factors – offenders, victims, geographical location and time – is significant in understanding crime events. Consequently, this can help in preventing or reducing crime occurrence. Environmental criminology theories attempt to understand these aspects; the following sections will introduce them in more detail.

2.2 Environmental Criminology

The previous section has introduced the geographical location as a crucial aspect of crime and highlighted its importance in crime analysis. This section will discuss environmental criminology to obtain a better understanding of the major theoretical aspects behind the generation of spatial crime patterns at particular times and places: routine activity theory (RAT) and crime pattern theory (CPT). This will incorporate the major objective of this study in understanding spatial patterns of MVT in Riyadh, SA.

Environmental criminology attempts to focus on the context surrounding a crime occurrence, such as offender and victim characteristics, the physical surroundings, and spatio-temporal aspects (Brantingham, P.J. and Brantingham, 2008; Boba, 2005; Chainey and Ratcliffe, 2005). In contrast to traditional criminological theories, environmental criminology does not try to explain why people tend to be offenders or what the main social causes of crime are (Boba, 2005). In environmental criminology, socioeconomic and demographic characteristics are important from the point of view of representing the location of (some) people involved in (some) crimes: while individual criminal tendency is influenced by factors such as emotional behaviour, inheritance and personal upbringing, it is also influenced by immediate environmental factors and surroundings (Cornish and Clarke, 2008). However, victim and offender characteristics have a much larger part to play in representing the characteristic daily routines of populations within the crime system. Environmental criminology is not, generally, a field that gives a detailed understanding of the life-stages and drivers of individual criminals. From an environmental criminology perspective, a crime event is the result of complex interactions between human behaviour and the environment (Wortley and Mazerolle, 2008).

The environmental criminology approach seek to explain how opportunities exist and come together in order for crime to occur (Boba, 2005). When the opportunity to commit a crime is present then crime happens (Boba, 2005). Opportunity is considered as the main cause of most crimes (Felson and Clarke, 1998). Furthermore, the pattern of crime opportunity varies from one crime to another so each crime has its own opportunity to occur (Felson and Clarke, 1998). For example, the pattern of opportunity for burglary from a dwelling is different that of motor vehicle theft.

A number of environmental criminology theories have been formulated from an environmental perspective. The most popular theories used in understanding crime from an environmental perspective are routine activity theory (RAT) and crime pattern theory (CPT).

Felson and Clarke (1998, p.v) stated that "*routine activity theory and crime pattern theory are helpful in understanding the concentration of crime opportunities at particular places and times*".

Both theories provide an understanding of spatial patterns of crime by linking the geographical location of a crime to its surrounding factors. The concept for routine activity theory (RAT) is explained by socioeconomic and demographic characteristics of neighbourhoods whereas the concept for crime pattern theory (CPT) focuses on characteristics of the built environment (Andresen et al., 2010). This is particularly relevant for studying motor vehicle theft (MVT), as both theories will provide different explanations for factors contributing to MVT occurrences, since these factors are apparently absent from the MVT literature in SA (see Chapter 3, Section 3.3).

The following sections attempt to explain the core elements of RAT and CPT. In addition, it will highlight the socioeconomic-demographic and physical conditions that were present during the formulation of RAT and CPT in order to provide the basis for considering the application of these theories to the Saudi Arabian context.

2.2.1 Routine Activity Theory (RAT)

RAT was proposed by Cohen and Felson (1979) and developed by Felson (1986). The theory was tested using crime statistics and socioeconomic, demographic and land use data from 1970 to 1974 (Cohen and Felson, 1979). The early 1970s were accompanied by an industrial labor revolution in the US. Thus, remarkable social and economic changes occurred in this decade, accompanied by increased crime rates in almost all Western countries (Young and Garland, 2002). Despite a reduction in unemployment and deprivation (which foster crime), RAT attributed this rise in crime rates to household social change (Cohen and Felson, 1979).

Throughout the 1970s, social and economic conditions notably changed in America. For example, families tended to live as single adults, the labor force increased, the percentage of employed married females increased and unemployment rates decreased (Cohen and Felson, 1979). Furthermore, during that era, the percentage of educated people and household income increased. This led to the growth of suitable targets (Cohen and Felson, 1979). Additional change in socioeconomic conditions – for instance, greater labor force and commuter participation – also resulted in an absence of capable guardians (Cohen and Felson, 1979). Moreover, as the proportion of the younger population grew, the age structure and its influence on activities changed. As a result of economic prosperity, there was also an increase in the availability of suitable targets and an absence of capable guardians. Hence, crime rates increased (Cohen and Felson, 1979). Based on the above information, the routine activity theory was deduced and formulated in the US.

The premise of RAT is that crime is more likely to occur if there is a motivated offender who finds a suitable target (victim) with no capable guardian. It assumes that people are inclined to commit crimes when given an opportunity (Cohen and Felson, 1979). However, when Felson (1986) developed the routine activity theory in 1986, he added the “handler” as a factor that keeps potential offenders from committing crimes.

The handler can be a parent, social commitment, personal belief and so on (Felson, 1986). Furthermore, the theory argues that the spatial and temporal patterns of people's activities can affect the three elements of the theory (likely offender, suitable target and incapable guardian) and consequently influence crime rates. The three components must therefore come together in place and time with the presence of appropriate situational conditions, such as physical features and social factors, to encourage a crime to happen (Felson, 1986). Temporal variation of crime incidents could thus be the result of variation in offenders' and victims' routine activities.

The routine activity theory also shows that people with certain socioeconomic characteristics are more likely to be victims of crime (Cohen et al., 1981). For example, single adult households that work and spend more time outside the home are at higher risk of victimization than large families and married couples(Cohen and Felson, 1979). This may be caused by an absence of capable guardians in empty houses, which encourages burglary. The theory attempts to say that people with these characteristics have lower or higher victimization rates as a result of their daily activities.

The application of RAT does mainly focus on burglary. It explains that burglaries increase in the daytime because people go work, leaving their homes (and many suitable targets) without a capable guardian (Cohen and Felson, 1979). When the theory was first developed by Cohen and Felson (1979), it used four types of crime to test its ideas. Specifically, data for forcible rape, aggravated assault, robbery and burglary that occurred in the US in 1973 was evaluated. These crimes were statistically significant and correlated to household activity rates, supporting the theory that routine activities influence crime rates. Motor vehicle theft, however, was excluded from the analysis due to a statistical issue because was highly correlated with the other predictors (Cohen and Felson, 1979). Thus, still, one may argue that people who spend more time outside of their homes are at a higher risk of being victims of crimes such as MVT.

The theory assumes that people have tendencies to commit crimes and have tendencies to be capable guardians (Felson, 1986). These tendencies to break the law and prevent crime, however, vary from person to person. Therefore, it is not essential to change the motivation of potential offenders to prevent crime. Rather, it is important to alter routine daily activities (Felson, 1986). Hence, any changes in people's daily activity will influence crime rates due to limited opportunities (Felson, 1986). The following Figure 2-1 provides a summary of how RAT was proposed and its elements developed.

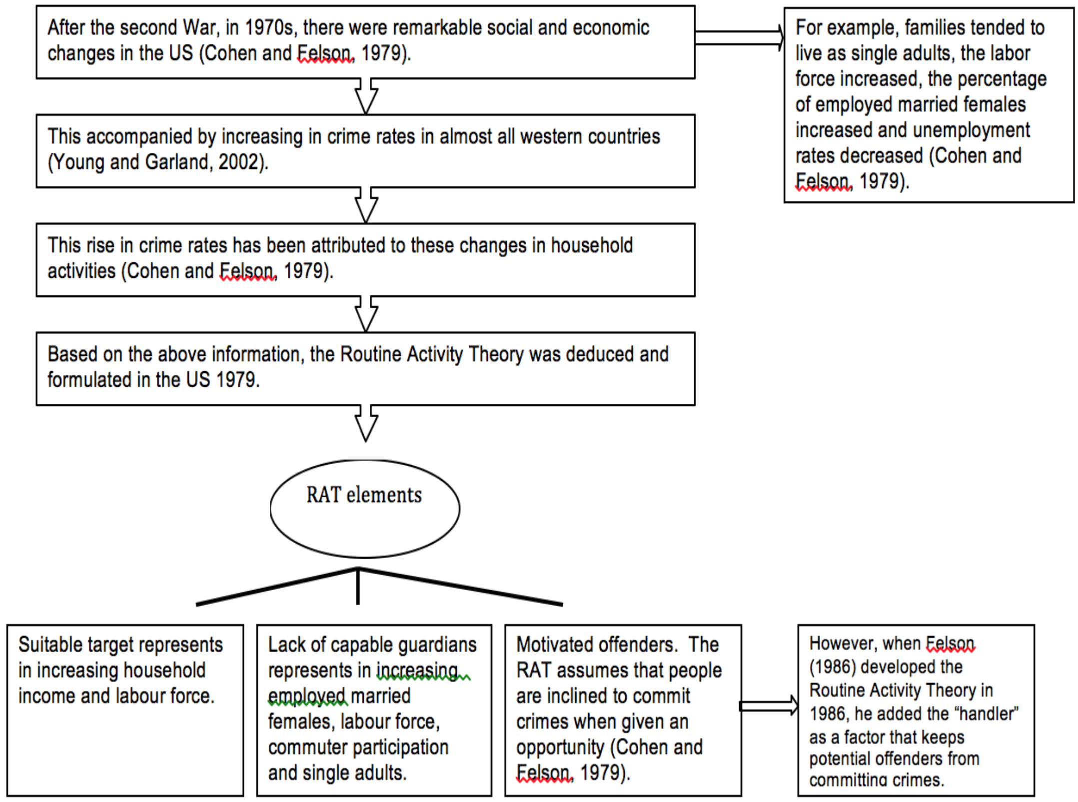


Figure 2-1: Showing a summary of the process of formulating RAT

2.2.2 Crime Pattern Theory (CPT)

CPT was introduced by Brantingham, P.J. and Brantingham (1993) in Canada, and was derived from combining some aspects of the theories that have already been proposed, such as routine activity theory (Cohen and Felson, 1979), rational choice theory (Cornish and Clarke, 1987; Clarke, R.V. and Cornish, 1985) and the geometry of crime theory (Brantingham, P.L. and Brantingham, 1981). Crime pattern theory shows how the complexity of the crime occurrence process, which starts from individual offenders taking decisions in daily life, creates a crime template that influences the potential offender's readiness to commit offence (Brantingham, P.L. et al., 2011). In addition, the decisions to commit a crime are influenced by triggering events and the potential offender searches for suitable targets against an environmental backcloth (Brantingham, P.L. et al., 2011; 2008; 1993). Based on the theory, if the daily activities of the potential offender intersect in a place with a likely target, then crime may occur (Brantingham, P.J. and Brantingham, 2008).

Crime pattern theory indicates that the crime patterns of criminals vary based on their daily life and their activities (Brantingham, P.J. and Brantingham, 2008; 1993). According to pattern theory, criminals are more likely to commit crimes in areas that are well known to them or they are aware of (Brantingham, P.J. and Brantingham, 2008; 1993b; 1993). The reason for this could be that criminals may feel more comfortable in the places known to them than other, new places (Brantingham, P.L. and Brantingham, 1993b). For example, an offender who lives in a neighbourhood categorized as a poor or ethnic area tends to commit crime in similar areas with the same characteristics (Chainey and Ratcliffe, 2005). Spatial awareness differs from person to person based on age and socioeconomic characteristics (Brantingham, P.L. and Brantingham, 1993b). For example, as was indicated by Eck and Weisburd (1995) criminals in their early years may tend to commit crimes near their own residence, which might be the reverse with older criminals.

CPT argues that high concentrations of clusters are likely to occur close to the activities nodes such as the subway station or bus stops and bars (Brantingham, P.J. and Brantingham, 2008; Brantingham, P.L. and Brantingham, 1993b). When patterns of victims overlap spatially-temporally with the patterns of offenders, crime occurs close to or in activity nodes of patterns of victims and offenders (Brantingham, P.J. and Brantingham, 2008). Areas or places that many people tend to be in or near, due to the activities that they have, such as shopping malls, provide opportunities for crime to occur; these are called *crime generators* (Brantingham, P.J. and Brantingham, 2008; 1995). Areas or nodes that attract potential offenders specifically to commit a crime are called *crime attractors* (Brantingham, P.J. and Brantingham, 2008; 1995). For instance, areas where vehicles are more likely to be left unattended might attract car thieves.

In summary, Section 2.2 has reviewed the core elements of the major environmental criminology theories – RAT and CPT – which will be utilised to explain MVT in Riyadh, SA. The review has revealed that the application of RAT focuses predominantly on burglary, whereas the setting of MVT occurrence received little consideration by these theories when they were formulated. Furthermore, this section has presented how these theories were proposed and developed within the socioeconomic-demographic and physical conditions in the West. These conditions contributed to formulating the core elements of the theories, and this should be taken into account when applying them. In this study, the aforementioned theoretical aspects will be critically discussed in Chapter 4.

Two fundamental areas have been highlighted by RAT and CPT in relation to understanding spatial-temporal patterns of crime. First, the time and location of crime tends to vary according to people's daily activities. Second, the concentration of crime at particular places and times is attributed to the presence of specific socioeconomic, demographic (related to motivated offenders, victims and guardians) and environmental features (related to attractive locations and activity nodes) that contribute to an increase in crime opportunities.

Having discussed RAT and CPT, the next section will discuss the use of spatial and statistical methods as they are essential tools for understanding the phenomena being discussed.

2.3 Spatial and Statistical Analysis Methods

This section will review both types – spatial and statistical methods – that are helpful in accomplishing the understanding provided by the principal themes of RAT and CPT. First, Section 2.3.1 will review spatial analysis methods that aim to explore variations in crime occurrences according to time and location. These spatial analysis techniques can identify and offer a greater understanding of crime patterns, examining the underlying processes that create these patterns (Chakraborty, 2000). They can be defined as a set of methods and models that "*explicitly use the spatial referencing of each data case*" (Goodchild and Haining, 2004, p.365) to generate new insight and understanding.

Second, Section 2.3.2 will review statistical and modelling methods that examine the relationship between the spatial patterns of crime and the factors that contribute to creating these patterns. The results obtained from implementing spatial and statistical analysis can be linked with empirical aspects of studies and theories to obtain an understanding of crime (Anselin et al., 2000). The final subsection will outline the general limitations of spatial analysis in this area (Section 2.3.3). These spatial and statistical analysis methods will be subsequently implemented to explain MVT in Riyadh and thus will be described in more detail in the Methodology Section 5.4, in Chapter 5.

2.3.1 Exploratory Spatial Analysis Methods

The first objective identified through reviewing RAT and CPT is to determine whether crime varies according to time and location. Two spatial analysis methods are employed in the criminology field to accomplish this objective. The first method maps crimes at different time periods and compares occurrences throughout the day. The second identifies statistically significant differences between these spatial patterns of crime at different time periods of the day. The following sections will discuss these spatial methods and their uses in criminology research, also highlighting their limitations, as they will be adopted in this study.

2.3.1.1 Crime Mapping

Mapping is a widely used technique in spatial analysis of crime (Ferreira et al., 2012). It aims to visualise spatial patterns of crime in order to describe the distribution of patterns to allow analysts to conduct more advanced analyses to explain causality behind these patterns (Brunsdon et al., 2007). Mapping can provide analysts with new insight into the spatial distribution of patterns through visualising the variations between these patterns in space and time (Brantingham, P.L. and Brantingham, 1998). The most appropriate map is one that communicates the information over clearly (Eck et al., 2005). Eck et al. (2000) suggests that the interpretation of crime maps can become effective and understandable if analysts have a clear theoretical perspective of crime mapping. Environmental criminology is considered a fundamental theoretical reference that supports the development of crime mapping (Chainey and Ratcliffe, 2005). In this study, the aim of mapping crime is to see if it tends to concentrate in certain neighbourhoods and at particular time periods of the day.

Thematic maps are most commonly used for displaying crime data aggregated to administrative boundaries (Chainey and Ratcliffe, 2005; Canter, 2000). They are appropriate for this study as it is conducted at a neighbourhood level for both crime rates and census data. Reno et al. (1999) pointed out that thematic maps are the most useful technique for showing crime rates and types of land use. A large number of published crime studies (Suresh and Tewksbury, 2013; Andresen, 2006b; Flowers, 2006a; Malczewski and Poetz, 2005; Akpinar and Usul, 2004; Ackerman and Murray, 2004) have used thematic maps for mapping crime.

However, the most significant limitation of this method is the shaded polygon (region) with colour, which can give the impression that the concentration of crime incidents extend over the whole region while in reality some parts of this region might have only a small number or no incidents (Eck et al., 2005; Chainey and Ratcliffe, 2005). Furthermore, this approach will face the significant issue of Modifiable Area Unit Problem (MAUP), as the results of aggregation for crime incidents are influenced by zonal effects, scale of area and its shape (Eck et al., 2005; Chainey and Ratcliffe, 2005). Another significant drawback is the ecological fallacy, when a decision is taken about an individual people based on aggregated data for a large number of people (Chainey and Ratcliffe, 2005).

2.3.1.2 Detecting Differences Between Spatial Patterns

The previous section has shown how spatial patterns of crime can be described in terms of their spatial distributions across the study area. However, these aforementioned maps cannot tell the extent to which a spatial pattern at a certain place and time is statistically different from other spatial patterns. This is a particularly important step in spatial analysis because according to the core concepts of RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) crime incidents tend to show higher concentrations at specific times and locations as a result of interaction between the daily activities of potential offenders and victims. Thus, this indicates that some areas have higher frequencies of crimes at specific periods, while other areas may have lower frequencies. Therefore, it is important to compare and differentiate between the two data sets of crime hotspots over different periods of time to detect significant differences in crime density. For example, if the distribution of spatial patterns of crime during two periods of time differs significantly, it is likely that the factors generating these patterns are also different. Thus, it will prompt crime analysts to investigate these differences using other statistical techniques such as regression models, which will be discussed in the following Section 2.4.2.

A method that can be used to achieve the previous analysis is the spatial point pattern test, which was developed by Andresen (2009). This technique is useful for determining statistically significant differences/changes between two crime data sets (Andresen, 2009). The spatial point pattern test has been recently used in different crime studies. Hodgkinson et al. (2016) implemented this test to detect the statistically significant spatial changes in MVT occurrences from 2003 to 2013 in Vancouver, British Columbia. The aim of using the test was to determine whether there was a reduction in MVT occurrences at the city level in Vancouver, or in some parts of the city, from 2003 to 2013. Similarly, Andresen et al. (2016) used this method to assess whether spatial patterns of property crimes from 2003 to 2013 were concentrated and stable within specific locations in Vancouver, while de Melo et al. (2015) adapted the test to investigate similarities in spatial crime patterns in Brazil. De Melo et al. (2015) differed from earlier studies by comparing similarities in the concentrations of different crime types in Campinas, Brazil, aggregated over four years (2010–2013). Andresen et al. (2010) used this method to examine the stability of crime patterns in Canada. The test enabled comparing the spatial patterns of different crime types at various scales of analysis to identify similarities and differences. Andresen and Linning (2012) used the method to detect statistically significant changes in spatial crime patterns at different scales in Canadian cities.

Working from a different perspective from these studies (Andresen et al., 2016; Hodgkinson et al., 2016; de Melo et al., 2015; Andresen and Linning, 2012; Andresen et al., 2010); Andresen and Malleson (2013) applied this test to identify similarities in the spatial patterns of crime types in Canada during different seasons (spring, winter, summer and autumn) and determine whether the occurrence of crime varied according to the seasons as routine activities changed, as suggested by RAT. The study yielded an interesting finding: crime that occurred during a certain season showed relatively different spatial patterns from other seasons (Andresen and Malleson, 2013). Andresen and Malleson (2013) used the test in a similar manner to the present study, but the present study will detect and identify significant differences between spatial patterns of MVT based on RAT and CPT at a lower scale of time (time periods throughout the day).

Overall, the spatial point pattern test seems to have been put to two general uses in the crime studies reviewed. First, most researchers applied this test to detect decreases, increases or stability in the occurrence of crime at certain places and times. Few researchers have used this test to identify significant differences between spatial patterns of certain crimes during different time periods in order to examine variations in crime opportunities across time and place.

Although this test has promising features as mentioned, it is similar to other spatial point pattern tools based on aggregating points into areal units. Consequently, the results from obtained the test are likely to vary according to the different geographical scales or zonal systems used (Ratcliffe, 2005; Fotheringham and Rogerson, 2004; Fotheringham and Rogerson, 1993).

2.3.2 Modelling Crime

The previous exploratory spatial analysis methods (Section 2.3.1) were reviewed to examine the first premise of RAT and CPT: that crime occurrence varies across space and throughout time due to variations in daily activities. The review of RAT and CPT in Section 2.2 suggested that certain factors, including socioeconomic, demographic and environmental variables, can significantly contribute to increased crime opportunities at certain places and times throughout the day. To understand the spatial patterns of crime, therefore, it is critical to determine the factors that contribute to the creation of spatial patterns. This knowledge is relevant for the major objective of this study to understand MVT under RAT and CPT.

Regression analysis is frequently used in criminology to achieve this goal as it can provide a better understanding of the spatial patterns of crime (Anselin et al., 2000; Maltz, 1995). This statistical method is designed to describe and investigate the relationships between a dependent variable (e.g. a crime type) and independent variables that can help explain and predict it (Field, 2009; Scott and Pratt, 2009). Regression methods are used in crime analysis to explain why certain areas have higher crime rates than others, allowing analysts to model the features of these areas and address these crimes (Scott and Pratt, 2009).

2.3.2.1 Ordinary Least Squares Regression (OLS)

One of the most useful technique in regression analysis is ordinary least squares (OLS) (Leung et al., 2000). OLS is a linear regression model that can be used to model a variable of interest as a dependent (response) and single or multiple variables as independent, sometimes called explanatory variables that may explain and predict the dependent variable (Hutcheson and Sofroniou, 1999). OLS can be applied to examine and predict crime occurrence at different locations and over different periods of time (Chainey and Ratcliffe, 2005). The OLS model is often used with a continuous dependent variable (Hutcheson and Sofroniou, 1999) such as crime rate. This is because count data often generate a statistical problem because they violate the assumption of OLS that the dependent variable is normally distributed (Du et al., 2012). One advantage of OLS regression is that it is an appropriate starting point before conducting spatial regression models to identify key variables (Charlton and Fotheringham, 2009; Scott and Pratt, 2009). This characteristic is important to this study, which will involve a spatial regression method, as discussed later in this Section 2.3.2.

The OLS regression model is widely used in crime studies. For example, Walsh and Taylor (2007b) used OLS regression to determine the relationships between MVT rates and community structure. Meanwhile, Rice and Smith (2002) and Copes (1999) modelled variables representing RAT to explain MVT rates using the OLS as a modelling technique. Further crime studies by Cahill and Mulligan (2007) used the OLS regression model to examine the relationships between violent crime and a number of socio-demographic variables. Ceccato et al. (2002) used OLS to identify the relationship between socioeconomic variables and crimes such as vandalism, theft of and theft from vehicles, and residential burglary.

The key limitation of the OLS regression model is its assumptions of normality, linearity and homoscedasticity, which will be discussed in more detail later in Chapter 5. These assumptions can be violated and produce biased results if they are not treated probably (Scott and Pratt, 2009).

2.3.2.2 Multinomial Logistic Regression (ML)

The second method for modelling crime throughout the day is to divide crime incidents into different time periods and to predict in which neighbourhoods crime incidents are most likely to occur at certain times. Multinomial logistic regression (ML) can accomplish this goal. Multinomial logistic regression (ML) is frequently used to predict the probabilities of more than two levels of a categorical response variable based on independent variables (Field, 2009). This method in contrast to OLS regression, multinomial logistic regression (ML) does not require the previous assumptions of OLS regression as normality, linearity and homoscedasticity (Wang et al., 2012; Starkweather and Moske, 2011), which makes it more usable by statisticians (Starkweather and Moske, 2011).

The ML regression method has been used in a number of crime studies. Recently, Andresen (2015) adapted the ML regression model to predict significant spatial clusters of different crime types, while Peng and Nichols (2003) used the method to predict levels of adolescent behavioural risk. A study conducted by Andresen and Jenion (2004) implemented the ML regression model in a somewhat similar manner to its use in this study for predicting crime throughout the day. They applied the ML regression method to predict the probability of burglary using variables suggested by social disorganisation theory and categorised burglary incidents into two-hour periods, creating 12 periods (categories) each serving as a dependent variable

(Andresen and Jenion, 2004). The categorisation of burglaries into 12 periods throughout the day was not based on criminology perspective but served the purpose of enabling a comparison of the ability of the ML regression method and aoristic analysis to predict the probability of crime occurrence (Andresen and Jenion, 2004). Two hours, though, is a too short a period to reflect the patterns of daily activities, so it cannot capture the spatial-temporal variations in crime occurrence throughout the day.

Applying the OLS and ML regression models requires consideration of two important statistical assumptions: multicollinearity and spatial effects. These assumptions are discussed in the following.

Multicollinearity

The first significant assumption is that there should be no or little multicollinearity between the independent variables for OLS (Pringle, 1981) or ML (Starkweather and Moske, 2011). This is because inclusion of independent variables highly correlated with each other in a regression model creates an overlap of the influence of these independent variables on the dependent variable (Leech et al., 2014). Thus, it will provide inaccurate coefficients; for example, the effect of multicollinearity can lead to a change in the effect of predictors – from a real positive prediction to false negative prediction – on the response variable (Yoo et al., 2014). Copes (1999) work provides a good illustration of the effect of multicollinearity on predictors. Copes (1999) modelled MVT rates using the OLS regression method and reported that high multicollinearity between variables changed the effects of some predictors; for instance, the positive effect of population density on MVT rates became negative. In a similar case showing the effect of multicollinearity, Andresen (2006b) used a spatial regression model to identify the relationships of 13 independent variables with MVT rates, burglary and violent crime under RAT and social disorganisation theory. Some explanatory variables exhibited high correlations, for instance, between the standard deviation of average family income and average income in thousands ($r = 0.78$, nearly $=0.8$). This very high collinearity between independent variables could have affected the estimations of the regression models.

Various solutions to overcoming the issue of multicollinearity include removing one of the highly correlated variables and using more popular methods, such as principal component analysis (PCA), to produce uncorrelated variables (Tu et al., 2005). PCA is a multivariate technique to reduce the number of predictor variables by producing a few independent components (Jackson, 2005). A number of crime studies have implemented this method as a reduction technique to overcome the effect of multicollinearity (Congdon, 2013; Willits et al., 2011; Morenoff and Sampson, 1997). However, a key limitation of this method is the probability that some information about the explanatory variables will be lost when producing the few components that represent the original variables (Piculescu, 2002). These components might also be difficult to define or interpret (Piculescu, 2002).

Spatial Effects

The second issue is related to the lack of attention to the spatial effects in traditional regression methods (Anselin et al., 2000). Spatial patterns have two critical considerations—spatial dependence and spatial heterogeneity (Chainey and Ratcliffe, 2005; Anselin et al., 2000; Anselin and Getis, 1992)—that are essential aspects of spatial analysis to consider to understand the creation of spatial crime patterns (Chainey and Ratcliffe, 2005). These effects are discussed as follows.

1. **Spatial Dependence**

   Spatial dependence indicates that the value of a place is dependent on the value of the place(s) next to it (Chainey and Ratcliffe, 2005; Getis, 1999). This situation occurs when locations with similar (or dissimilar) values are surrounded by locations of similar (or dissimilar) values; otherwise, these cases are considered to be independent of each other (Chainey and Ratcliffe, 2005). The concept of spatial dependence arises from the first rule of geography: '*everything is related to everything else, but near things are more related than distant things*' (Tobler, 1970, p.236). In the criminology field, spatial dependence can exist between the values of dependent variables; for instance, a neighbourhood with a high crime rate might be surrounded by nearby neighbourhoods which also have high crime rates. Spatial dependence can also exist between independent variables; for example, a neighbourhood with a high unemployment rate might be surrounded by areas with high unemployment rates.

   Spatial dependence can affect the results of traditional regression methods as they are based on the assumption of independency between the residuals (Bernasco and Elffers, 2010). Spatial statistics then are essential for analysts to check for spatial independency between the residuals. Importantly, the presence of spatial dependency in the OLS residuals does not suggest that the OLS estimates are biased but, rather, that the examined explanatory variables are not sufficient to produce the best linear regression model due to bias in variance of the residuals (Bernasco and Elffers, 2010; Anselin, 2001). In addition, the presence of spatial dependency in the OLS residuals can suggest that the regression model does not include a key explanatory variable (Rosenshein et al., 2011). This is a very interesting point, which adds another advantage for detecting spatial dependence amongst residuals. Thus, this detection of spatial dependence offers an effective way of comparing the performance of OLS regression models. This, in turn, is particularly useful for this study to assess the ability of variables to represent theories for predicting MVT rates throughout the day, and thus assessing the performance of regression models.

Spatial autocorrelation is considered to be a measurement of the spatial dependence between the values of observations (Getis, 2010; O'Sullivan and Unwin, 2010; Eck et al., 2005). Spatial dependency in residuals is detected using a global measure of spatial autocorrelation, which is a single value that examines whether the value of an observation at a spatial unit is independent of the values of that observation at neighbouring spatial units over the entire study area (Getis, 2010; Anselin et al., 2008). Global Moran’s I is the most frequently used statistical method for measuring global spatial autocorrelation (Bernasco and Elffers, 2010; Chainey and Ratcliffe, 2005). The main advantage of this method is that it can be used for both types of crime data, as points or aggregated at polygons (Chainey and Ratcliffe, 2005). This method also supports flexible uses (Bernasco and Elffers, 2010). Crime studies by Desmond et al. (2010) and Chainey and Ratcliffe (2005) used global Moran’s I to detect spatial autocorrelations between the residuals in OLS regression models and found that they were spatially autocorrelated. In contrast, Wallace et al. (2006) detected random spatial autocorrelation of the residuals, and thus it was not necessary to conduct a spatial regression.

2. Spatial Heterogeneity

The second consideration in spatial patterns is heterogeneity, which refers to variations in the distribution of the occurrence of incidents across the area studied (Anselin et al., 2000). Furthermore, heterogeneity can suggest variation in the spatial relationships between the dependent variable of interest and the independent variables over the study area (Anselin et al., 2000). Spatial heterogeneity is a very important element of the spatial analysis of crime patterns, enabling detecting variations in crime rates and identifying the causes, which could be the inconsistent effects of each factor (e.g. social, economic, demographic and physical variables) on crime rates over the study area (Chainey and Ratcliffe, 2005). Whereas most traditional statistical models are based on linearity and assume that variables are stationary processes, the spatial patterns of factors, such as the physical environmental, are not linear and vary by area (Maltz, 1995; Maltz, 1994). Traditional regression methods, such as OLS, assume that explanatory variables equally influence dependent variables at every place throughout the study region. Their influence, though, does not remain the same across the whole area as an independent variable might act differently in various places due to variations in environmental factors (Chainey and Ratcliffe, 2005; Anselin et al., 2000).

A number of spatial regression techniques have been developed to take into account the issue of spatial effects; spatial dependence and spatial heterogeneity between observations (Anselin et al., 2000). The most commonly used spatial regression method is geographically weighted regression (GWR) (Bruna and Yu, 2013). GWR is an explanatory and local technique that fits a regression for every feature (polygon) and its neighbours in a study area. It enables analysts to consider the process of spatial non-stationary (Brunsdon et al., 1996). It permits the relationships among observations to vary over the study area (Leung et al., 2000).

GWR has been applied in a variety of crime studies. For example, Cahill and Mulligan (2007) adapted it with comparison to OLS global model to explore the spatial relationship between violent crime and different explanatory variables that might explain causes of violent crime in Portland, Oregon. They found that GWR could provide useful results since it shows variation between variables over the study area and indicates the variability in violent crime across the study region. However, GWR has been criticised because it is vulnerable to the effect of outliers of values as the presence of outliers can bias estimation of the regression coefficients (O'Sullivan and Unwin, 2010).

The following sections will provide a summary of the common limitations that could influence the usefulness of the introduced spatial and statistical techniques.

2.3.3 General Limitations of Spatial Analysis Methods

There are significant impediments that influence the use of spatial analysis techniques leading to reduction of their advantages in crime field. A range of problems may arise when spatial patterns of crime are aggregated into areal units. The first is the Modifiable Areal Unit Problem (MAUP) that emerges when the results of statistical analysis of the same spatial data vary from one location to another within the study area due to the variation in the geographical scales or zonal systems (Ratcliffe, 2005; Fotheringham and Rogerson, 2004; Fotheringham and Rogerson, 1993). The zonal effects refer to the variation in statistical results within a set of areal units due to the different systems that have been applied to aggregate these units at a similar scale and number of areas but with variations in the geographical boundaries (Wong, 2009). The scale effects refer to the changes in the statistical results due to different levels of scale when decreasing or increasing the size of the scale (such as from county to wards)(Wong, 2009).

Most spatial analysis applications are vulnerable to the influence of changes in partitioning systems and scale levels (Fotheringham and Rogerson, 1993). The influence of this problem might be clear in traditional statistical techniques such as correlation results are dependent on the scale level and zoning systems (Wong, 2009). Wong (2009) highlighted that at a small-scale level the outcomes of association between variables can show negative relationships. When the same data are aggregated at larger geographical units, the results may indicate strong positive relationships. Attempts have been made to resolve both sources of the MAUP but the best solution is to obtain micro level data, which might be difficult to obtain due to issue of confidentiality (Weeks, 2004).

The second problem is the ecological fallacy that occurs due to making inferences about individuals within the study area on the basis of statistical results obtained from data about aggregates (Wong, 2009; Chainey and Ratcliffe, 2005). For example, an analysis of burglary rates in a city might show that areas with high burglary rates correlate with areas having residents belonging to lower-income groups and might infer that people belonging to lower-income groups commit burglaries, though they might be caused by other variables. One of the solutions to reduce the effect of such ecological fallacies, similar to MAUP, is to aggregate the data of such socio-economic variables and crime rates to a lower geographical scale.

Another important issue in spatial analysis is the influence of edge on the study area. Spatial data and their values that are located outside the study boundaries can affect the values of spatial data which lie within the studied area due to the presence of spatial autocorrelation (O'Sullivan and Unwin, 2010; Fotheringham and Rogerson, 1993). Edge effects are a common concern for crime analysts due to restrictions in police district boundaries (Ratcliffe, 2005). Different suggestions have been made to correct for edge effects. One of the simplest ways is to create a guard area around the boundary of the study region (O'Sullivan and Unwin, 2010; Ratcliffe, 2005). A limitation of this solution is the determination of the best relevant distance for the guard zone around the edges to include significant points that may influence the events inside the study regions (Ratcliffe, 2005).

Taken together, Section 2.3 reviewed the spatial analysis process for understanding crime under two major ideas of RAT and CPT. To assess the premise that crimes tend to occur at specific places and certain times, exploratory spatial analysis methods (the mapping technique and spatial point pattern test) were reviewed in Section 2.3.1. The second type of methods reviewed is aimed at detecting the underlying factors that contribute to concentrations of crime at certain time and places. To accomplish this objective, the use of regression methods (OLS, ML and GWR) for modelling crime was reviewed in Section 2.3.2. This section concluded with a discussion of several possible limitations due to the nature of spatial data, such as edge effects, geographical scales and zonal systems (Ratcliffe, 2005; Fotheringham and Rogerson, 2004; Fotheringham and Rogerson, 1993). These spatial and statistical methods will be explained in Chapter 5 in more detail, with particular emphasis on how they will be applied in the spatial analysis of MVT in Riyadh, SA.

2.4 Chapter Summary

This chapter has explored and explained the spatial analysis of crime patterns, providing a foundation for this study through a review of two areas of literature: the theoretical framework of environmental criminology and analysis methods for crime patterns. The reviewed theoretical framework highlighted the importance of geographical location in tackling crime and showed that crime incidents are likely to be concentrated at specific places and certain times as a result of specific factors (Anselin et al., 2000; Eck and Weisburd, 1995; Roncek, 1981). A wide range of factors related to the characteristics of geographical locations can make specific areas more vulnerable to types of crime than other areas (Eck et al., 2005).

Section 2.2 reviewed the environmental criminology theories RAT and CPT and their core elements. Both theories emphasise that crime opportunities do not occur equally throughout the day and across space as some neighbourhoods have higher crime risks and rates at particular times than other areas, as discussed. RAT and CPT offer insights explaining the underlying causes of the concentration of spatial crime patterns at these places and times. Furthermore, the review showed that both theories were originally developed in the West within specific cultural, socio-economic and physical contexts, and the empirical tests of these theories were conducted primarily using burglaries. Therefore, we will investigate the applicability of both theories to explain MVT in SA, later in Chapter 4.

Whilst Section 2.2 established the theoretical understanding of spatial crime patterns over space and time, Section 2.3 described the spatial and statistical approaches that can be implemented to attain this understanding. Section 2.3 reviewed the spatial and statistical methods related to two major ideas of RAT and CPT in explaining crime occurrences: first, the concentration of crime occurrences at certain places and at particular times of the day and, second, the specific factors that contribute to these concentrations. Section 2.3.1 focused on the use of mapping techniques and the spatial point pattern test to identify variations in spatial crime patterns across space and times of the day and to determine the statistical significance of these variations. Identifying significant differences between spatial patterns throughout the day and across the study area leads to investigating factors whose influence varies according to daily activities. Thus, the next step in spatial analysis is to conduct regression analysis to understand how these patterns are created.

Two types of regression analysis models, OLS and ML regression, were discussed. Numerous studies have implemented these regression methods to examine the relationships between a certain crime type and a number of explanatory variables. Two important issues, however, should be taken into account when using these conventional regression models: multicollinearity and spatial effects. This review revealed that high multicollinearity could lead to bias in the estimates of regression models (Leech et al., 2014; Yoo et al., 2014). PCA has been used in various studies to overcome the problem of multicollinearity amongst the independent variables (Congdon, 2013; Willits et al., 2011; Morenoff and Sampson, 1997).

Second, turning to the issue of spatial effects while conducting classic regression methods, spatial dependency and spatial heterogeneity can affect the results. GWR has been widely used as a spatial regression model to combat spatial autocorrelations in regression residuals and to take into account spatial heterogeneity (Bruna and Yu, 2013). Moreover, as briefly discussed in the final section 2.3.3, the analysis of spatial patterns often suffers from a number of issues and challenges mostly related to the nature of spatial data, such as the aggregation of data and the use of different scale levels (Ratcliffe, 2005; Fotheringham and Rogerson, 2004; Fotheringham and Rogerson, 1993). An important finding from this review of spatial and statistical methods was that lack of research investigating crime occurrences throughout the day according to the patterns of daily activities, as suggested by RAT and CPT, despite the importance of doing so. This study, therefore, will make a significant contribution to this area of research and improve understanding of why MVTs are more likely to occur across the study area and throughout the day.

RAT and CPT, which were developed in Western contexts, are applied in this study to explain MVT in SA, particularly Riyadh. To this end the following chapter will discuss the context of SA, particularly its social, demographic, cultural, legal characteristics, crime rates and literature.

Chapter 3
Saudi Arabian Context

3.1 Introduction

The previous chapter reviewed the spatial theories and methodologies applied in the environmental criminology field in order to better understand the spatial patterns of crime. RAT and CPT were formulated and developed within a Western context but are applied outside their original context in SA in this study. Therefore, it is important to build a sufficient understanding of the SA context to determine which, if any, existing challenges should be taken into account when applying these theories to it. The aim of this chapter is to understand the SA context and make relevant comparisons to Western contexts. This chapter is crucial in achieving the overall research aim to understand MVT in Riyadh under RAT and CPT.

To fulfil this goal, Section 3.2 firstly compares SA and Western socioeconomic, demographic, legal, cultural and physical characteristics. The factors that contribute to variations within a countries' crime rates are discussed in Section 3.3, which also provides an overview of crime in SA, focusing on MVT and how differences in the SA context result in different MVT than in Western countries. Section 3.3 also provides a critical review of the literature on the geography of crime and MVT to identify existing knowledge about crime in SA, particularly MVT, which improves understanding of MVT under the selected theories. The final sub-section 3.3.5 reviews the current policing efforts and practices to tackle MVT in SA in order to identify what this study can contribute to improve the SA policing efforts.

3.2 Characteristics of Saudi Arabia

This section will focus on the characteristics of SA in terms of socioeconomic, demographic, legal, cultural and physical factors. It will particularly illustrate the characteristics that participated in the formulation of RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.J. and Brantingham, 1993) in the West (see Chapter 2, Section 2.2). These characteristics are more likely to affect the behaviour of offenders and victims in SA. Therefore, the comparison between SA and the West will identify differences/similarities that will be subsequently discussed in Chapter 4 to evaluate their influence on the applicability of the theories. To achieve this goal, this section will start with a brief introduction of the Kingdom of SA before outlining Saudi characteristics in the following subsections.

Saudi Arabia is situated in the west of the Asian continent. The Kingdom of SA measures an estimated 2,150,000 km^2 with a population of nearly 27 million (see Figure 3.1) (Central Department of Statistics and Information, 2010). The study area is Riyadh, which is the capital city of the Kingdom of Saudi Arabia (KSA). It lies within Latitude 38.24°N and Longitude 43.46° E and is about 600 meters above sea level, and located in the middle of Saudi Arabia (High Commission for Development of Riyadh, 2009).

According to the official census carried out in 2010, Riyadh's population is approximately 5,188,286 this is a growth of approximately 22% since 2004 (4,260,000) (Central Department of Statistics and Information, 2010).

Figure 3-1: A map showing Saudi Arabia and the capital –Riyadh City.

Source:(Qhtani and Al Fassam, 2011)

SA has a range of key features that make it substantially different from typical Western contexts. The following sub-sections attempts to identify these regional differences in order to discuss their effects on the applicability of RAT and CPT later.

Here we focus on the UK, US and Canada in our definition of 'Western', but most of the relationships hold across Western Europe and other industrialised countries. Future work might use a more nuanced definition of 'Western', but this is beyond the scope of this study.

3.2.1 Socio-Demographics

The demographic structure of SA differs in a number of respects from the West. Firstly, the majority of Saudi's population is young. About 70% of the population was under 29 years old in 2007 see Figure 3-2 (Central Department of Statistics and Information, 2008a), while approximately 38% of the UK's population was under 30 years old in 2008 (Office for National Statistics, 2009) and in the US, about 40% of the population was under 29 years old in 2010 (United States Census Bureau, 2015). The Saudi population aged between 5 and 24 is the largest cohort, and as population becomes older, the size of the age cohorts decreases. In contrast, the largest age cohorts in the US and UK are aged between 30 and 55 (Office for National Statistics, 2015b; Howden and Meyer, 2010).

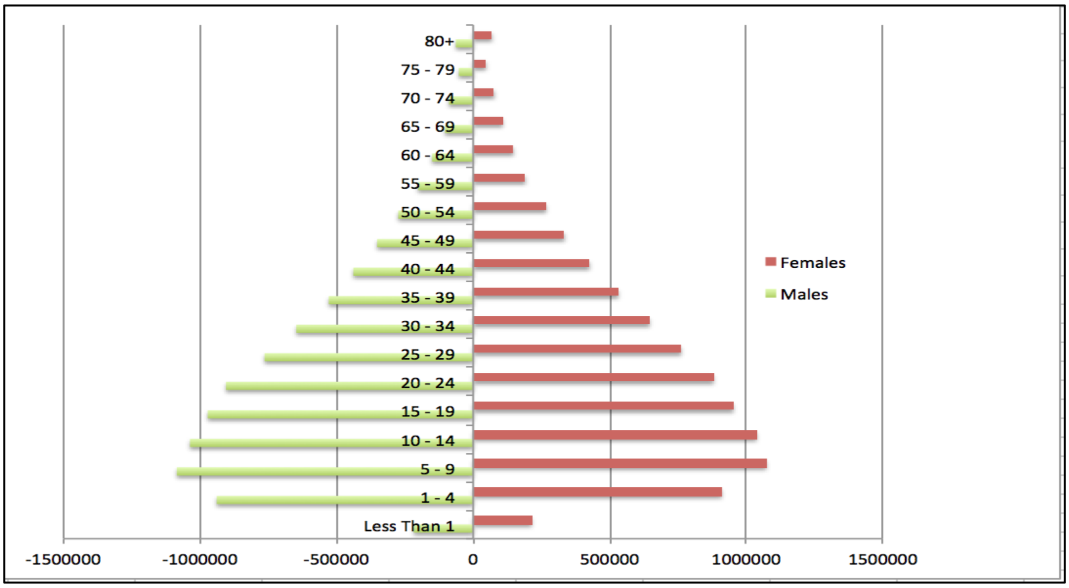


Figure 3-2: A population pyramid for Saudi population in 2007
Source: (Central Department of Statistics and Information, 2007)

SA has a larger proportion of foreigners who come to the country to work; they constituted 30% of the population in 2007, making up nearly 55% of the labour force (Central Department of Statistics and Information, 2008b). Furthermore, 70% of non-Saudis are male and the majority of them are aged between 29 and 39 (Figure 3-3) (Central Department of Statistics and Information, 2007). Hence, the percentage of males in SA is 57% of the total population (Central Department of Statistics and Information, 2010). In contrast, the gender balance in the US and UK is more balanced at – 49.2% male; 50.8% female – for both countries (Office for National Statistics, 2015a; Howden and Meyer, 2010).

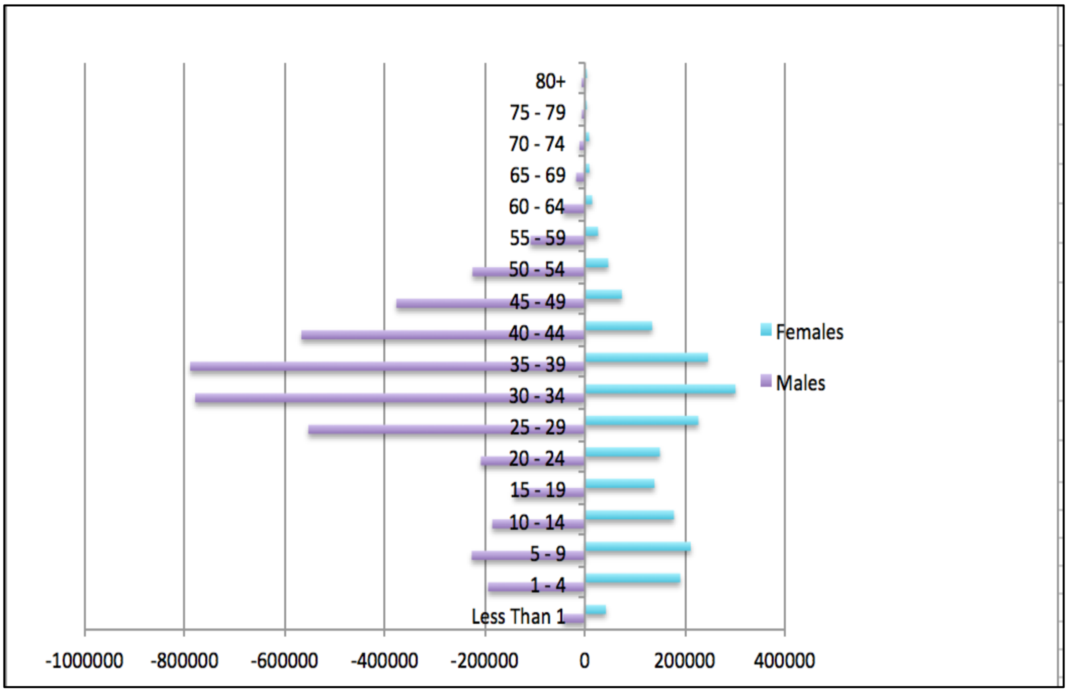


Figure 3-3: A population pyramid for non- Saudi population in 2007
Source: (Central Department of Statistics and Information, 2007)

In SA, the proportion of females in the labour force is very low in comparison to Western countries. The percentage of females in the labour force was only 14.3% in 2011, while in the UK and the US in 2011, females accounted for 46.1% and 46% respectively (The World Bank, 2016). Furthermore, in 2009, just 11% of married women were in the labour force in the SA (Central Department of Statistics and Information, 2009), whilst in the UK and US the percentages were 72% in 2013 (Office for National Statistics, 2013b) and 69.1% in 2011 (U.S.Bureau of Labor Statistics, 2013) respectively. Moreover, the average family size in SA was about six people in 2012 (Central Department of Statistics and Information, 2012) compared to 3.14 people in the US in 2010 (Lofquist et al., 2012), 2.3 people in the UK in 2012 (Compton, 2013), and 2.4 people in Canada in 2016 (Statistics Canada, 2017). In Western countries, it is more common for people to live singly; young males and females often leave the parental home at an earlier age of about 20 years (Office for National Statistics, 2014; Reher, 1998) which can weaken family ties (Reher, 1998). In contrast, Saudi families tend to live together, with much strong family ties (Qari et al., 2013).

Although there are substantial socio-demographic differences between SA and Western counties, there are some similarities. Most relevant here is that the average number of vehicles per household is similar: 1.7 in SA in 2010 (Central Department of Statistics and Information, 2010), 1.8 in the US in 2013 (Feng and Luo, 2016), and 1.2 in the UK in 2011 (White, E., 2012).

3.2.2 Legal Systems

An important legal distinction is that SA adapts and implements Sharia (Islamic law) for all legislations and regulations, including criminal justice (Ali, 1985). Sharia is taken from the Muslim holy book "*Quran'* and from *'the sayings, actions and approvals of the Prophet Muhammad*" called "*Sunnah*" (Aasi, 2003,p.727). Islamic law (Sharia) aims to preserve the five basic needs of the individual: maintaining religion; maintaining the soul; maintaining the mind; maintaining descendants and morals; and maintaining property (Al-Bashar, 2001). Crime in Islamic law can be defined as a series of prohibitions that God has enjoined by kisas or hadd or tazir (Ḥumayd, 1979). Based on the previous definition, crime in Islamic law can be classified according to three main types: hadd, kisas and tazeer. Hadd crimes are acts that have been identified in the holy Quran and carry specific punishments (Al-Bashar, 2001). The hadd crimes considered as serious offences include (Al-Bashar, 2001) :

- Apostasy from Islam
- Theft
- Adultery
- Defamation; false accusation of adultery or fornication
- Robbery
- Drinking Alcohol

The second classification is kisas crimes that have also been identified by the holy Quran and the Sunnah (Al-Bashar, 2001). It includes, for example:

- Murder (premeditated and non-premeditated)
- Premeditated offenses against human life, short of murder
- Murder by error; offenses by error against humanity

The third type of crime is tazir, which includes the remaining acts that are not included in the previous classification as hadd or kisas. The holy Quran does not specify any punishments for tazir crimes (Ḥumayd, 1979). Thus, tazir can be defined as the crimes and sanctions which are left to be determined by the leaders of Islamic society with a specific goal of reformation and correction (Ḥumayd, 1979).

Since SA implements Sharia law, there are important differences in the SA legal systems when compared to Western countries. In the West, some acts are classified as legal but would be illegal under the Sharia, and vice versa. For example, same sex-marriage is allowed by law in the US (2004) and England and Wales (2014) (Freedom To Marry, 2016). In contrast, homosexuality is still illegal in SA. Furthermore, drinking alcohol, which is illegal and punishable by law in SA (Sa'ud, 1984), is legal (albeit regulated) in other countries. As another example, polygamy is legal in SA and illegal in the US and the UK. These differences in criminal justice lead to variations in crime rates between countries, particularly for certain types of crimes, such as crimes against morals, religion and beliefs.

Driving regulations present some substantial differences and are particularly important for this study. According to the Saudi traffic legislation, women are not allowed to drive. For clarity, it is worth detailing that women found to be driving cars would not be considered to have stolen them: it is formally the crime of driving without a licence. There is the potential for women to steal cars, but in practice young males have been reported to account for the majority of MVT (Roberts and Block, 2012; McCaghy et al., 1977). Hence, females do not make up a numerically significant element of offenders, and the population can be taken as male when examining offender behaviour.

3.2.3 Weekly Routines

The Hijri calendar (H) is the official calendar in SA. It is based on cycles of the lunar phase. Until July 2013, Thursday and Friday were the official weekend days in SA, after which the system switched to Fridays and Saturdays. The working day is usually 7 hours; from 7:30 a.m. until 2:30 p.m. In SA, as in many Muslim countries, there are specific days and months that have religious significance for Muslims. The most popular religious times are Ramadan, which is the ninth month of the Hijri calendar; Eid Alfater, which comes after Ramadan month ends; and Dhu Al-Hijjah, which is the last month of the Hijri calendar.

As with religious and/or cultural holidays in other countries, these have a substantial impact on the routines of residence and hence the occurrence of crimes. There is strong empirical evidence for this in SA. For example, during Ramadan the working hours change from seven hours to five, and run from 10 am through to 3 pm as fasting during the day and general celebrations make for busier social lives in the evenings. The traffic volume that indicates the movement of vehicles to and from home, work, shops and leisure, can be used to illustrate the patterns of daily activities. Figure 3-4 illustrates the considerable differences in traffic volumes during the month of Ramadan for Riyadh in 2011 compared to normal days.

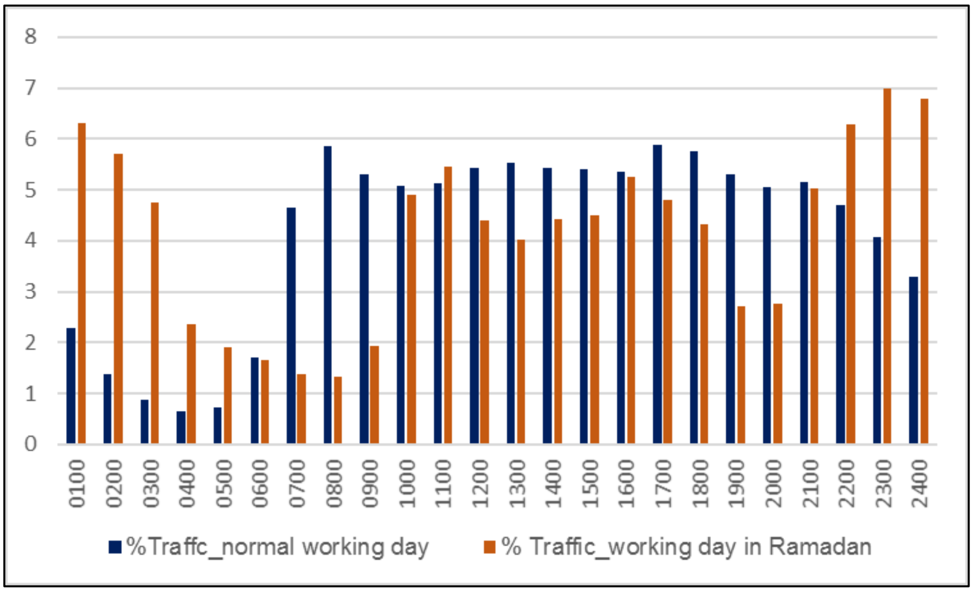


Figure 3-4: A bar chart showing the percentage of vehicle traffic for the working day on a normal day and during Ramadan in Riyadh.

Source: (High Commission for Development of Riyadh, 2012).

Figures 3-5 and 3-6 show traffic volumes for the US and UK. It can be seen that the trends for the traffic volume are similar in the two countries. The highest traffic volumes during periods of commuting are in the morning between 6 am and 8am and the evening between 4 pm and 5pm. Then the traffic decreases noticeably from 6 pm to reach the lowest levels in the early morning. This coincides with traditional working hours: Monday to Friday, approximately 9 am to 5 pm. These patterns of traffic volumes clearly indicate that Saudi daily patterns of activities are different from those for the British and Americans. For example, by comparing the traffic patterns, people in SA tend to do some activities using vehicles during the evening time as the traffic volume is high until 9 pm, whereas in the UK and US during the working days the traffic patterns show only high traffic volumes during the commuting periods. This may suggest that most people tend to stay at home in the evening or at least they are not using vehicles for their activities. Note, also, that the diurnal double-peak is not present in the SA data – SA traffic peaks quickly and remains high throughout the day, perhaps reflecting the lack of public transport, which in the UK and US would be used by the economically inactive during non-commuting times thereby reducing counts of individual vehicles during these times.

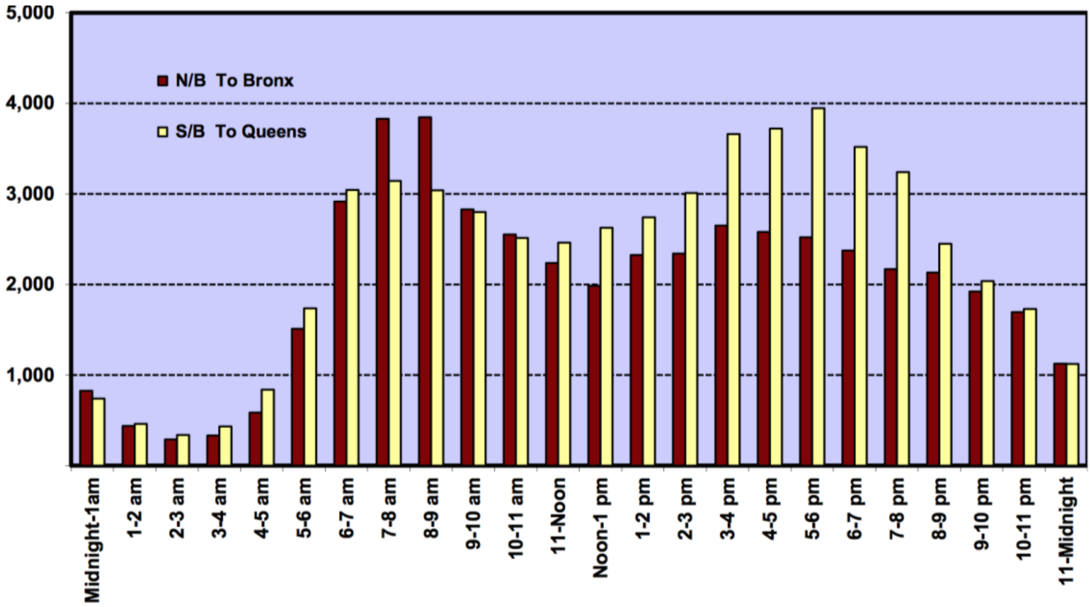


Figure 3-5: Hourly traffic volumes on Bronx-Whitestone Bridge, New York in the US in 2010. **Source:**(Sadik-Khan, 2012).

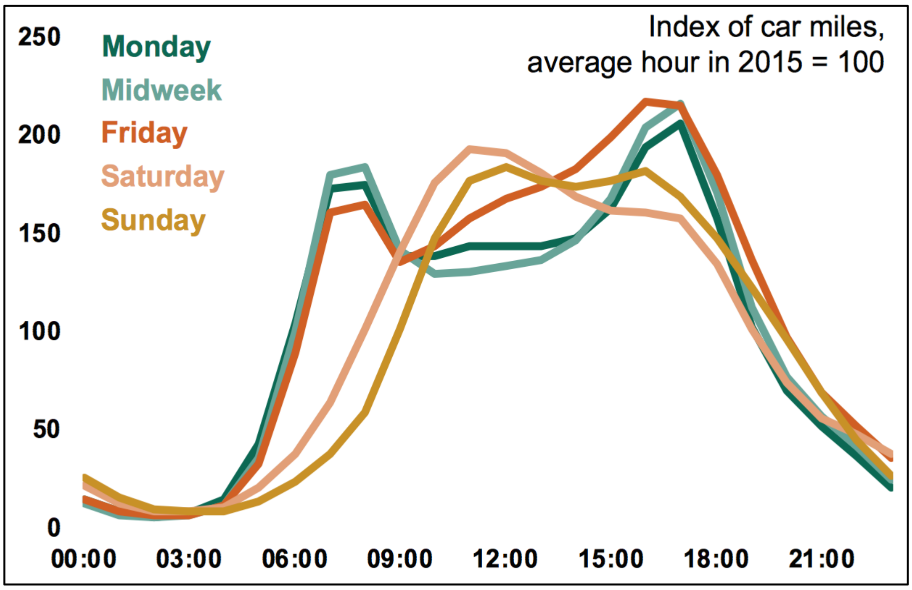


Figure 3-6: Daily car traffic trends on all roads in the UK. **Source:** (Department for Transport, 2016).

3.2.4 Built Environment

SA and Western countries differ not only in these socioeconomic factors but also in the physical environment. For example, vehicles are the main form of transportation in SA due to the lack of bus and train systems within its cities. This goes to some degree to explaining the considerable gridlock that develops across the city during the day. It is worth noting that in Riyadh, the capital city; there is a large Metro rail system currently under construction. A further important characteristic of the built environment in SA is that there is a lack of established paths for cycling or walking inside the residential areas, particular in Riyadh, the focus of this study. This characteristic could be attributed to the desert climate conditions in SA. Figure 3-7 shows a street view of a residential area in Riyadh as an example, which clearly demonstrates that no footpaths or pavements are available to pedestrians.

Figure 3-7: A street view of a residential area in Riyadh. **Source:** (Alotaibi, 2017a)

Another difference between the built environments is the architecture. In SA, a house is more likely to be surrounded by a walled-in courtyard, with the wall at least two meters high for privacy (See Figure 3-8).

Figure 3-8: Street view shows houses and parked cars, Riyadh, SA. **Source:**(Alotaibi, 2016).

Furthermore, in SA, there is a high density of facilities, such as grocery stores, shops, laundries and restaurants, along roads in many residential areas. Due to the desert climate in SA, some people tend to leave their vehicles running while they are paying. Figure 3-9 below shows cars waiting outside behind other vehicles next to a wide range of facilities. This situation can facilitate opportunities for MVT, as will be discussed later in Chapter 4.

Figure 3-9: Shops, grocery stores, restaurants and offices distributed along the street of a residential area in Riyadh. **Source:** (Alotaibi, 2017b)

To summarise, Section 3.2 has shown the main characteristics of SA compared to its Western counterparts. It is clear that there are substantial differences in terms of socioeconomic, demographic, cultural, legal and physical characteristics. These contribute to formulating the behaviour of offenders and victims, as well as daily activities and the geographical location of crimes. Thus, the differences between the characteristics of SA and Western countries can also significantly affect crime statistics.

As we have identified the contextual variations where theories will be applied, the following step before applying these theories is to obtain some understanding about the levels of crime in Saudi Arabia and the existing body of research on crime and MVT in particular.

3.3 Crime in Saudi Arabia

This section attempts to review crime in SA in terms of statistics, literature and police practice, with a focus on MVT with comparison to the West. This will help in understanding the level of crime in SA in general and how the extent of the MVT problem in SA compares to key Western countries. Furthermore, the critical review of the SA literature about crime will identify where major questions remain and how this study will add to the existing body of research in SA, particularly in the area of MVT.

Before comparing crime rates between countries, it is vital to indicate that there are numerous factors that may affect crime statistics in any country. These factors should be considered when undertaking cross-national studies in crime and justice. Rates of different types of crimes in different places in the world might be influenced by a number of significant factors. First, awareness of crime prevention programs and an understanding of preventive safety measures vary from person to person and also from one community to another. For example, crime studies in the United Kingdom have shown that males between the ages of fifteen to twenty-four years have a higher risk of victimisation (European Communities, 2004) and are more likely to commit crimes (Jansson and Britain, 2007). Hence, crime prevention strategies could pay more attention to this demographic by increasing awareness of crime and by reducing the causes that encourage this group to become involved in crimes themselves. In some countries, the population may have better awareness of crime prevention measures because of programs implemented to improve the awareness of those at risk, which can help reduce crime rates in these communities (European Communities, 2004).

Therefore, certain groups of people in certain places might be more vulnerable to specific types of crimes than other groups (Harries, 1973). Another factor that causes variations in crime rates and types is religiosity, which has been highlighted by a number of studies (Brauer et al., 2013; Serajzadeh, 2001; Al-Khalifah, 1994). Religiosity can be defined as religious commitments, such as prayers, in the personal lives of religious people (Gunnoe and Moore, 2002). It has been found that religiosity has a negative relationship with crime rates (Brauer et al., 2013). The religiosity of a community can enhance moral values that help inhibit crimes (Brauer et al., 2013).

A further factor that can be considered as contributing to a variation in crime rates is that the abilities and effectiveness of police forces are not equal, and vary from place to place (Harries, 1973). A police force might benefit from studies in crime analysis for tackling crimes (Boba, 2005), which differ from one country to another based on the availability of sufficient and accurate data from reliable sources. Another cause of differing crime rates across regions is a variation in the ability of police forces to implement the law in different areas (Harries, 1973). The feeling of justice and fairness by people and the effectiveness of police forces in catching offenders may help to reduce incidents of crime (Souryal, 1988). Additional considerations in making comparisons between countries based on types and volumes of crimes are the different legal and criminal justice systems adopted by various countries, differences in the constitution of crime, how the police record offences and which offences are not recorded (Clarke, S., 2013). Even variations in the quality of a country's crime research should be considered. For instance, some studies attempt to use crime data based on prisoners. This may be misleading since data gathered from prisoners can be significantly influenced by factors such as different court systems and the effectiveness of these courts, in addition to differing sentence lengths (Clarke, S., 2013). A number of other critical variables contribute to variations in crime rates between regions, including age, gender, ethnicity and other socio-demographic factors, land use and weather (Harries, 1973). The influence of these variables on occurrences of crime might be apparent since these factors are not evenly distributed over space (Harries, 1973).

Despite the presence of the aforementioned circumstances and their effects on crime records, a comparison could still be useful if it is made to investigate variations in the factors that cause crime in different countries and to examine what might encourage or prevent the occurrence of crime. We can also benefit from knowing how these factors work in one country and considering their influence in another. For the purposes of this research, the following sections attempt to provide an overview of crime statistics and literature in SA, with some relevant comparison to crime statistics in the UK, the US and Canada. In addition, the current practices of Saudi Police forces in tackling MVT will be discussed.

3.3.1 Crime Statistics in SA

Throughout the last two decades, rates of recorded crime have increased in SA. Official Saudi statistics indicate that crime reported in 1413H (1992) was 229,864 incidents, which is 1361 crimes per 100,000 population reaching 454,304 incidents in 1434H (2013), 1476 crimes per 100,000 population i.e. increasing by nearly 11% (Ministry of the Interior, 2014). In spite of this increase, the number of crime incidents/crime rates in SA is still considered to be relatively low in comparison to other countries. For example, in the US, statistics indicate that the rate of violent crime was 372.6 offences per 100,000 population, and the property crime rate was 2,487 offences per 100,000 population (FBI, 2016). While, in England and Wales, the estimated rate of violence against the person was 1500 offences per 100,000 population, and property crime was 5287 offences per 100,000 population in 2010/11(Chaplin et al., 2011). Furthermore, according to the United Nations Surveys on Crime Trends and the Operations of Criminal Justice Systems in 2010, several types of crime in SA were classified as having the lowest rates in comparison to other world countries, including burglary (in 2002), robbery (in 2000), assault (in 2002), kidnapping (in 2002) (Harrendorf et al., 2010) – although it is important to recognise that some of these differences might be partly an artefact of differences in national legal systems or in reporting/recording practice as previously discussed. Nevertheless, the definition of MVT crime varies little internationally, and in SA it was classified as medium rate in 2002 (Harrendorf et al., 2010).

Going down to the city level, the official crime statistics for the capital city of SA, Riyadh, reported 53,045 incidents during the period 1431H (≈2010), which is 10.2 crimes per 1,000 residents. Meanwhile, the number of crimes decreased during 1434H (≈2013) is 43,375 incidents, which is 8.3 crime per 1000 residents. Furthermore, the official crime statistics revealed that property crime accounted for the highest percentage of types of crime incidents that occurred in Riyadh during the period 1430H to 1434H (2009 to 2013). It made up nearly 45.1% followed by violent and physical crimes making up 16% of total crimes (Police Department in Riyadh, 2014).

3.3.2 Studies on the Geography of Crime in SA

Little research on SA has attempted to understand crime from a geographical perspective (i.e. by considering the spatial patterns of offending as well as other factors). This scarcity of research has been pointed out by a number of researchers (Almatrafi, 2005; Al-Bashari, 1999; Alwelaie, 1993). Al-Bashari (1999) indicated that this scarcity could be attributed to the difficulties that researchers face in gathering data about crime. The available literature on the geography of crime that has emerged from SA suffers from the absence of a wide range of significant data elements in general and those that focus on MVT specifically. The following sections will critique the available literature, highlighting the importance of research that is well grounded in sound theoretical perspectives.

Existing studies in SA have been primarily focused on the characteristics of offenders rather than victims, the geographical location of crime incidents or its surrounding factors. Table 3-1 below summarises the few relevant studies that are available. There are a number of limitations and weaknesses with the current state of the research field, which are important to consider. They will be summarized in the following paragraphs.

A major criticism of Alwelaie (1993) is the lack of theoretical contextualisation for examining variables that influence each type of theft crime. The regression model could explain only 23% of the variations of MVT using the land use variables. This weak model result suggests key explanatory variables in the environmental backcloth were missing from the analysis and/or the underlying population at risk was problematic. The latter issue certainly plays out in the study as the denominator used to calculate rates was resident population, and it is clear this only acts as a proxy for the real population of potential victims (volume of available cars: Weisel et al., 2006; Ceccato et al., 2002) at certain times of day. A further limitation of Alwelaie (1993) is that, despite attempting to examine the relationship between different types of theft crime and land use characteristics for each district, the study did not show the locations where the types of land use influence different types of theft rates over the study area.

Although Al-Khalifah's (1997) work is one of the most comprehensive for crimes carried out in Riyadh (the capital of SA), it too generates only a weak explanatory model for crime. The author examined the relationship between 27 independent variables and property crime rates, and found only one variable (the percentage of households who were foreign workers) that was statistically significant. The model explained only 10% of crime theft in Riyadh. In part, this is because the study aggregated all property crimes, though underlying this issue is the fact that, in spite of introducing a number of criminology theories – e.g. Anomie Theory, Cultural Conflict Theory, Social Disorganisation, and Opportunity Theory – the study ultimately does not use crime theory to conceptualise the model. A more developed theoretical framework would have dictated against aggregating all property crimes into a single measure as the important variations in motivational and contextual factors that are present in different types of property crime would have been more apparent.

This aggregation issue, which disguises the nuances in the crime system, is also seen in the study by Aldawsari (1997). In addition, it focuses solely on the characteristics of prisoners rather than the surrounding environmental and victim contexts. Aggregation, though spatial rather than between variables, is also an issue with Al-Kharif (1998), who explored occurrences of different types of crime in 58 Saudi cities for the period 1407H (1986) to 1413H (1992). His study was carried out at a macro-analytic level that ultimately masked key spatial scales of variation likely in crime systems.

In view of all that has been mentioned so far, it is apparent that these existing studies on the geography of crime in SA to date suffer from limitations in terms of the particular theoretical perspective applied, data used, and methods adapted.

Table 3-1: Saudi studies on the geography of crime

Study	Aim	Scale	Data	Methodology	Key findings
AlMarzougi et al. (1986)	To determine the relationship between the social, family, educational and economical characteristics of prisoners and their relation to types of crime in SA.	Macro level	Interviewing criminals in prisons in SA	Simple statistical tests	A large number of prisoners were young, unmarried, low qualified, unemployed and had lived in instability with families on low incomes.
Alwelaie (1993)	Investigating the variations in spatial distributions of different types of theft crime across Riyadh's districts.	Micro level research	Crime statistics / interviewees with prisoners	Regression analysis and thematic maps	Most theft in Riyadh occurred in daytime, day of the week or monthly trends showed no variations. The characteristics of the prisoners based on the sample 34% were workers, 20% were unemployed, 97.2% were male and 50.4% aged between 25 and 39.
Al-Khalifah (1997)	Examining the relationship between crime rates among Riyadh's neighbourhoods and socio-economic demographic variables for neighbourhoods	Micro level research	Crime statistics/ socio-economic demographic variables for Riyadh's neighbourhoods	Traditional statistical methods, such as Pearson's correlation and multiple regression	Crime rates in Riyadh were positively correlated with unemployment rate, poverty level, unstable family and a proportion of young males. In contrast, crime rates negatively correlated with factors including high levels of qualification and higher income families (Al-Khalifah, 1997)
Aldawsari (1997)	Exploring the spatial distribution of crime in Jeddah and identifying social, economic and educational characteristics of criminal prisoners in Jeddah's prison.	Meso- analytic level	Crime data at police districts in Jeddah, on interviews with a sample of prisoners.	Regression analysis and creating thematic maps to display crime rates.	Theft crimes were the highest among other types of crime, making up 48.7% of total crimes. The highest proportion of prisoners were non-Saudis. The criminals who were aged from 25-30 years presented the highest percentage of criminals (31.4%). Additionally, the high proportion of criminals interviewed were males, unmarried, unqualified, unemployed.
Al-Kharif (1998)	Exploring occurrences of different types of crime in 58 Saudi cities for the period 1407H (1986) to 1413H (1992).	Macro-analytic level	Crime statistics, population data and interviewees with prisoners	Traditional statistics such as stepwise regression analysis.	Saudi cities with high population density and a high percentage of non-Saudis tended to have higher MVT rates. The proportion of Saudi arrestees was lower than non-Saudi arrestees within the studied cities. About 60% of those arrested were aged between 19 and 36 and the highest proportion unmarried and unemployed.
Mahya (2003)	Investigating the relationship between population density and crime rates at police district levels	Meso-analytic level	Crime statistics and population data	Using Pearson's correlation to measure this relationship.	The relationship between population density and crime rates was positive while there was a negative relationship with distance from the centre of the city.
Almatrafi (2005)	Identifying the spatial distribution of theft crime in Makkah and the characteristics of a sample of prisoners in Makkah	Micro level research	Crime statistics and interviewees with prisoners	Traditional statistical methods, for instance a chi-squared test	Arrested offenders reported committing crimes between 6 pm and 12 am. The majority of prisoners were characterized by low educational levels, were unemployed and unmarried.

3.3.3 Motor Vehicle Theft

There are various terms for car theft used in literature, for example, motor vehicle theft, auto theft, and automobile and car crime. The variation in motor vehicle theft terminologies could be due to the existence of different legal definitions for cars thefts in every country. Therefore, it is critical to specify a terminology that will be used consistently through this thesis. In the United States, motor vehicle theft comes as a subcategory of property crime (Federal Bureau of Investigation, 2011b), and it is categorized as motor vehicle theft. The Uniform Crime Reporting (UCR) Program defined motor vehicle theft as "*the theft or attempted theft of a motor vehicle*"(Federal Bureau of Investigation, 2004,p.35), while according to the Home Office in the United Kingdom, motor vehicle theft is a branch of vehicle offences and is described as "*Theft or unauthorised taking of a motor vehicle*" (Home Office, 2014,p.9) and as "*taking motor vehicle or other conveyance without authority*" (Home Office, 2014,p.8).

The Saudi legal system classifies motor vehicle theft as a type of property crime and defines it as the taking of a motor vehicle by a person who does not have authority to access it, including the temporary possession of a motor vehicle without authorization (Police department in Riyadh, 2014). Based on sharia law, motor vehicle theft is considered a tazir crime by the Saudi criminal justice system (see Section 3.2.2). In this thesis, the terminology of "motor vehicle theft" (MVT) is predominantly used.

MVT is not just a single type of offense; rather, it can be divided into three main types based on the purpose of the theft. According to Challinger (1987) there are three main classifications of motor vehicle theft that are derived from the motivations of the offenders (committing); joyriding, transport and making profits. The first is joyriding, which is probably primarily committed by young people (Clarke, R.V., 2002; Fleming et al., 1994). The second type is the theft of a motor vehicle for either temporary use in order to commit another crime, such as drug smuggling and robberies, or for personal use (Lyons and Teigen, 2008). Third type is stealing a motor vehicle to gain profit in different ways, for instance, by selling it as a whole or as spare parts (Clarke, R.V., 2002). Furthermore, sometimes this third type is actually fraud committed by the owner for the purpose of claims against insurance companies (Clarke, R.V., 2002; Henry and Bryan, 2000; Fleming et al., 1994; Clarke, R.V. and Harris, 1992). It has been indicated that nearly ten percent of motor vehicle theft incidents are thought to be frauds aiming for claims from insurance companies (Lyons and Teigen, 2008).

These categories could explain why some countries have more motor vehicle thefts than others; some countries have more joyriding, others more fraud, others more drug smuggling, and so on. Knowing the motivation of motor vehicle thieves is an important factor for tackling each category specifically. Motivations and means of committing vehicle theft, and the types of vehicles targeted, can influence theft rates within regions (Lu, 2006). However, there might be a lack of relevant data available on these categories of motor vehicle theft (Higgins, K., 1997; Clarke, R.V. and Harris, 1992). This might be because this kind of information is taken from arrested criminals; therefore, a number of studies have conducted interviews with arrested offenders to collect their information. However, the fact that a large proportion of offenders in most crimes are not arrested leads to a lack of overall information about offenders (Whitehead, 2012). The current study also suffers from the limited availability of data related to types of motor vehicle theft and offenders. Therefore, this study will focus predominantly on MVT as one type of crime.

Over the last two decades, MVT has accounted for the largest proportion of property crime incidents in SA. A study by Alwelaie (1993) indicated that MVT in SA constituted the largest proportion of property crime, accounting for 24.7% of all property crime during the period of 1406H to 1411H (≈1985 to 1990). MVT incidents in SA have increased significantly in recent years, making up 31% of all property crime occurring in 1435H (≈ 2014) (Ministry of Interior, 2015). Despite the general reduction in reported property crime in 2015, MVT incidents rose to make up 34% of all property crime in 1436 H (≈2015) (Ministry of Interior, 2016). The second highest occurring property crime is burglary, which accounted for 12.6% of property crime in 1435H (≈ 2014) (Ministry of Interior, 2015) but decreased to 10.9% in 1436H (≈2015) (Ministry of Interior, 2016).

In Riyadh, the MVT has made up the majority of property crimes for decades. MVT accounted for around 29.1% of all property crimes during the period of 1406H to 1411H(≈1985 to 1990) (Alwelaie, 1993). The recent official statistics (Figure 3-10) reveal that MVT made up 48.2% of property crime incidents in Riyadh for the period of 1430H-1434H(≈2009 to 2013), followed by burglary from a dwelling, pickpocketing and theft from vehicle, representing 10.8%, 10.3% and 7.4% respectively. In contrast, crimes such as assault on public property, arson and embezzlement show a low occurrence among crime against properties – accounting for 0.01%, 0.2% and 1.6%

respectively.

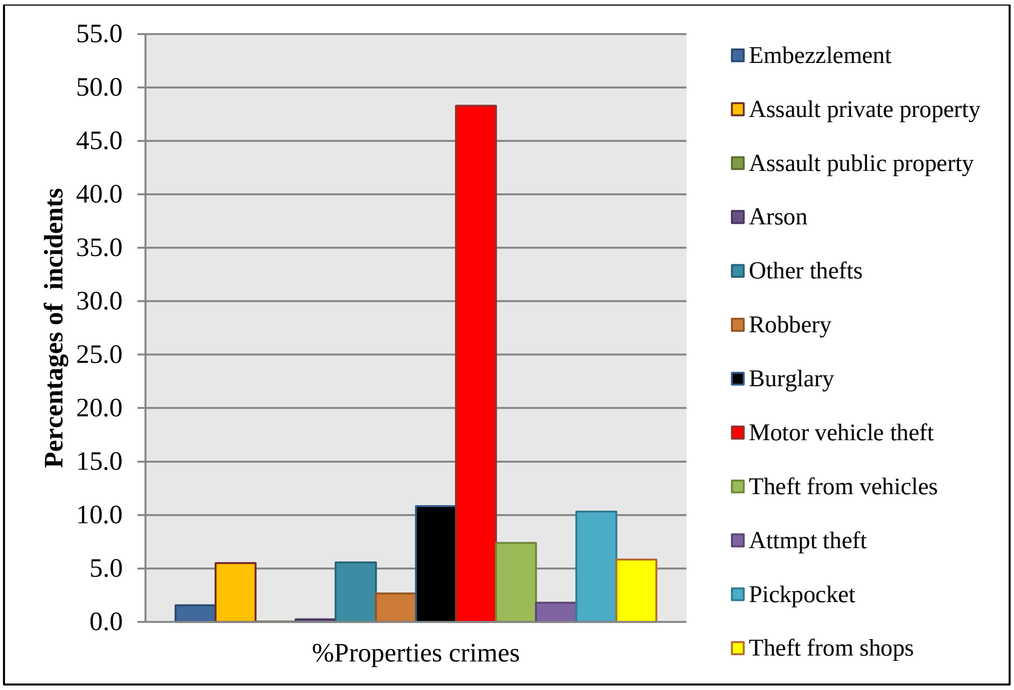


Figure 3-10: The percentages of properties crimes in Riyadh, 1430H to 1434H(≈2009 to 2013)

Source: Researcher's calculations based on data from the Police Department in Riyadh, 2014.

When a comparison is made between the levels of motor vehicle theft in SA and Western countries, such as the US, the UK and Canada, a stark contrast can be seen. We are aware of the differences in legal systems, definitions of crimes, approaches to crime classification and variations in police recording, as these have been previously mentioned. Nevertheless, in the US in 2015, larceny-theft accounted for 71.4% of property crimes, and this was followed by burglary, which accounted for approximately 20%, whereas motor vehicle theft made up about 9% of property crimes (FBI, 2016). Official crime statistics in the US indicate that MVT accounted for between 12.7% of property crime in 1993 and 8% of property crime in 2012, whereas burglary accounted for about 23% of property crime during the two-decade period (FBI, 2013). Meanwhile, in England and Wales, motor vehicle theft decreased steadily since 1974, from accounting for 13% in 1974 (Home Office, 2012) to 3.7% in 2010 (Office for National Statistics, 2012). Meanwhile, criminal damage accounted for the largest component of property crime in 2010, at about 24%, with burglary accounting for nearly 18% (Office for National Statistics, 2012). In Canada, in 2006, theft amounting to $5000 or below accounted for 52% of property crimes, whereas motor vehicle theft accounted for 13.6% and burglary 21.4% (Silver, 2007).

Overall, we can conclude that MVT has accounted for the majority of property crime in SA for decades. Conversely, MVT has constituted a lower proportion of property crime in Western countries. The following section will provide a critical review of the literature on MVT to identify existing knowledge about MVT in SA.

3.3.4 MVT Studies in SA

A small number of criminology studies have conducted research analysing MVT within SA. These are primarily concerned with the characteristics of incarcerated offenders. A study by Al Angari (2002) conducted interviews with 5,441 convicted cars thieves in SA. He found that the majority of criminals had low educational levels, lived in poverty and were unmarried (Al Angari, 2002). A key finding from Al Angari (2002) work revealed that vehicles stolen while left unattended on the street with the engine running accounted for a higher proportion than vehicles stolen when parked outside victims' houses. Research by Al-Qahtani (2008) interviewed teenagers who had committed MVT and been imprisoned in the Riyadh Social Care Centre. The study found that 68% of the sample stole vehicles for joyriding, and about 76% of the sample indicated that victims left their vehicles unprotected.

Work by Al-Shaheen (1996) interviewed juveniles who had committed car theft and were imprisoned in the Riyadh and Jeddah Social Care centres. The study revealed that most of the sample reported living in unstable families (Al-Shaheen, 1996). An important finding by Al-Shaheen (1996) revealed that juveniles indicated that they tended to target unprotected cars with the keys in the ignition. Moreover, work carried out by Al-Otaibi (2002) examined the views of Riyadh secondary school students towards car theft. Its main findings indicated that most of the students interviewed thought people might commit car theft in order to bring more attention to themselves or to seem more likeable (Al-Otaibi, 2002).

The previous studies are typically based on interviewing convicted car thieves. Unfortunately, this population is likely to be at best of dubious representativeness, and at worst biased. The population within prisons is likely to be a small sample of the overall MVT offender population. The proportion of arrested car thieves varies according to the police effort (Boba, 2005). Perhaps most critically, MVT has been reported to have a very low clearance rate. For example, in the US, only 11.9 % of motor vehicle thefts were cleared by arrest or exceptional means (Federal Bureau of Investigation, 2012a). In SA, the percentage of arrests for car theft during the period 1990 to 1992 was 6% (Al-Kharif, 1998), and 11.6% of the total reported MVT was in the Riyadh region in 2013 (Police Department in Riyadh, 2014). This would not matter if the sample was representative; however, Bryant (2012) has pointed out that the very low clearance for MVT leads to difficulty in identifying the characteristics of car thieves and generalising the results yielded from the sample taken from arrestees could be misleading (Boba, 2005). Furthermore, the studies are based on sub-samples which are often selective. For example, Al-Qahtani (2008), Al-Otaibi (2002) and Al-Shaheen (1996) interviewed car thieves who were juveniles, but not those who were older.

In conclusion, it is clear from the literature reviewed herein that most studies analysing MVT, in SA have primarily focused on the characteristics of offenders. There will be a range of significant elements contributing to motor vehicle theft spatial patterns that the current literature does not address. Obviously, these should be further examined and appropriately studied with a grounding in the theoretical frameworks developed within environmental criminology. Having identified the research efforts in studying the phenomenon of motor vehicle theft, the following section will outline the police efforts for combating MVT in SA.

3.3.5 Police Practice in SA

As previously stated, motor vehicle theft is a major problem in SA, so it is crucial to identify the efforts made to combat it. Identifying this will ultimately determine how this thesis can contribute to the current police efforts, which will be discussed later in the recommendation section in Chapter 9. Current police practice and legislation in SA to combat MVT can be classified into two categories: regulation efforts and fieldwork efforts. Saudi's Public Security has agreed with the Saudi Standards, Metrology and Quality Organization (SASO) to require some protection standards for imported vehicles to make them much harder to be stolen (Public Security, 2016). Public Security Sector in SA has a wide range of tasks to maintain public security for the population and the country, and one of these is to take all necessary measures to prevent MVT in SA. According to Public Security (2016), imported vehicles should have:

- Installed devices that prevent the vehicle being started without the original key.

- A car alarm as a warning system that produces a voice or light warning when any theft is attempted.
- A locked steering wheel when the key is not in the ignition.
- A serial number structure – the Vehicle Identification Number – to be visible within different parts of vehicles to identify them and make it more difficult to sell parts.

Furthermore, Public Security has implemented some regulations at the local levels (Public Security, 2012):

- Facilities should operate security forces and security systems such as surveillance cameras to protect these facilities from thefts.
- Car shops, car dealers, motor salvage dealers and scrap shops should make sure of the identity of sellers and their ownership of the vehicles or their parts.

The police's field efforts to tackle MVT are as follows (Public Security, 2012):

- Increased patrols and detectives in business districts and during the night and holiday periods elsewhere.
- Cooperation with Interpol to track exported stolen vehicles or parts of these vehicles, as well as car thieves.
- Cooperation with police forces in some friendly countries to exchange experiences in combating MVT.
- Cooperation with researchers and stakeholders in studying MVT.
- Cooperation with legislators/lawmakers to discuss how the punishment and deterrent of motor vehicle theft can be improved according to Sharia law.
- Improvement of the criminal justice statistics in terms of accuracy and reliability.

On the other hand, in the UK, crime prevention strategies for tackling MVT have focused on reducing or preventing opportunities for MVT by improving vehicle security (Morgan et al., 2016). This has been very successful. Crime statistics for MVT indicate that since improving the security of vehicles in the 1990s, MVT has decreased considerably (Morgan et al., 2016; Home Office, 2016; Farrell et al., 2011b). For example, the Home Office (2016) revealed a reduction in MVT incidents by 88% since

1995, referring to the critical role of security devices such as electronic immobilisers. Morgan et al. (2016) attributed the reduction in motor vehicle theft recorded in England and Wales to two security devices: steering locks and electronic immobilisers.

Effective measures for reducing the opportunities for MVT occurring can be seen in Canadian studies. Studies by Saville and Murdie (1988) and Dauvergne (2008) were both carried out in Canada. Saville and Murdie (1988) study, which was based on a police report from 1984, indicated that MVT was concentrated in areas that had vehicles with poor security levels, such as car dealerships and rental agencies. More than two decades later, recent Canadian statistics (2007) on MVT showed that car dealerships and car rental agencies had a very low percentage of motor vehicle theft incidents, accounting for only 1% of all auto thefts in Canada (Dauvergne, 2008). This large reduction of MVT could be attributed to the fact that police have improved security levels to protect vehicles parked in these facilities from thieves (Dauvergne, 2008).

These effective measures in improving the security of vehicles and car facilities contributed considerably in reducing MVT in Western countries such as the UK and Canada. However, although SA has applied a number of preventive measures, as indicated by Public Security (2016), MVT increased between 2014 and 2015 (Ministry of Interior, 2016). Public Security (2016) indicated that large numbers of vehicles were being stolen when the ignition keys were left in the vehicles . This drives us to investigate where and when MVT is more likely to occur and to understand the characteristics of locations that attract potential car thieves, examining how vehicle theft opportunities vary from place to place and time to time based on people’s daily activities. The finding of this study will help police forces predict where and when MVT will occur. This will help in concentrating police resources and efforts at certain times and places.

In summary, this section has found that the crime statistics in SA differ considerably from those in the West. Motor vehicle theft has accounted for the majority of property crime in SA and its capital city, whereas MVT constitutes a lower proportion of property crime in the major Western countries. Despite MVT continuing to be a problem in the Kingdom of SA, there is a lack of research investigating MVT, and the existing research has primarily focused on the characteristics of car thieves. Therefore, this research addresses this substantial research gap. In order to determine how this thesis can contribute to improving MVT prevention strategies in SA, the section has concluded with an overview of the current police practices for combating MVT .

3.4 Chapter Summary

This chapter has explored the Saudi context, including demographic, social, economic, cultural and legal factors. The findings demonstrated that the SA context is substantially different from Western countries. For example, the lower female labour force participation, large family size and young population of SA are all significantly different than the West. In addition, SA applies different legal systems, such as the prohibition of alcohol consumption and not allowing women to drive. Differences are apparent not only in the socioeconomic and demographic characteristics but also the built environment. For instance, in SA, there are no established footpaths in residential areas, vehicles are the main mode of transportation, and the design of houses also differs.

These contextual differences lead to different crime statistics as well (see Section 3.3). In a notable example from crime rates, MVT accounts for the most property crime in SA but a small share in the US, UK and Canada. Thus, it is clear that MVT is a major problem in SA, particularly in Riyadh. Despite this, very few studies have investigated this problem, and those that have primarily focused on the characteristics of car thieves (Al-Qahtani, 2008; Al Angari, 2002; Al-Otaibi, 2002; Al-Shaheen, 1996). Moreover, research on the geography of any type of crime is lacking. This situation lead to the key objective of this study: to examine the phenomenon of MVT in greater depth and to contextualise it within the theoretical frameworks developed in environmental criminology. To identify what specific contributions this study could make to improve existing MVT prevention strategies in SA, the countermeasures taken to prevent MVT in SA, such as improving vehicle security systems (Public Security, 2016), were reviewed.

Identifying the contextual differences, the MVT problem in SA and the lack of knowledge of the causes of the spatial-temporal pattern of MVT in SA drives us to ask whether these contributing factors in SA are similar to or different from those in Western countries. Furthermore, can these theories formulated and developed within Western contexts be applied to explain the MVT problem in SA? Answering these questions is critical to understand the spatial patterns of MVT in SA. The next chapter will explore how environmental criminology theories have been used to explain MVT in the West and evaluate how these theories can be applied to explain MVT in SA.

Chapter 4

Motor Vehicle Theft and Environmental Criminology Theory

4.1 Introduction

The empirical model of this study is underpinned by the theoretical frameworks developed in environmental criminology. Three major elements of these theories were reviewed in Chapter 2 (the geography of crime, spatial theories and spatial analysis techniques) to build a comprehensive picture of the current theoretical and methodological frameworks of the analysis of crime patterns. Chapter 3 explored the SA context where these theories and methodologies are applied in this study. This work needs to be related to the empirical studies on MVT. Therefore, the main goal of this chapter is to determine to what extent Western environmental criminology approaches, specifically RAT and CPT, have been explicitly acknowledged and applied in MVT research in the West and can be adapted to the SA context.

The chapter begins with a critical review of empirical studies on MVT in Western countries from the field of environmental criminology (Section 4.2). It explains the range of factors influencing MTV according to the premises of RAT and CPT. The objective of this chapter is not to revisit in detail the theory introduced in Chapter 2 but to explain how these theories shape the criteria determining the variables examined in this study's empirical model. Section 4.3 stands as the last theoretical discussion in this thesis, critically exploring the potential challenges to applying these theories to explain MVT in SA. This section focuses on the concepts of RAT and CPT, the characteristics of the contexts where these theories were developed, their existing applications to MVT and lastly the SA context where they are applied in this study. These findings refine the scope of research according to the study context and provide guidance for every aspect of the empirical work presented in chapters 5, 6, 7.

4.2 Existing MVT Studies in Western Countries

How have these theories been applied to MVT in the West? In general, MVT have been studied less than the other major crimes and within that body of work there are few studies utilising an explicit theoretical framework. A number of Western studies have noted this limited research on MVT (Suresh and Tewksbury, 2013; Lockwood, 2012; Walsh and Taylor, 2007a; Fleming et al., 1994), particularly in the area of the spatial patterns of MVT (Piza et al., 2016; Lu, 2006). Here, then, we take a more general approach. We have reviewed the major studies in this area (Roberts and Block, 2012; Walsh and Taylor, 2007b; Andresen, 2006b; Lu, 2006; Rice and Smith, 2002; Henry and Bryan, 2000; Copes, 1999; Rengert, 1997; Kennedy and Forde, 1990; Messner and Blau, 1987). The following sub-sections will critically review how MVT has been influenced by a range of factors according to the premises of routine activity theory and crime pattern theory. This will help identify the important factors that influence MVT, which will be used later in the empirical analysis for this study.

4.2.1 Routine Activity Theory

This sub-section will critically review the existing Western studies on MVT on the basis of RAT's elements: motivated offenders, suitable targets and absence of capable guardians (Cohen and Felson, 1979).

4.2.1.1 Motivated Offenders

Age is a key factor in criminality that has been found to influence the mobility of criminals (Eck and Weisburd, 1995), the types of crime committed and the awareness of space (Brantingham, P.L. and Brantingham, 1993b). Young males under the age of 18 have been found in different studies to account for a large proportion of arrested auto thieves. For example, in the U.S., it was reported in 1988 that those arrested for vehicle theft who were under 18 made up 40% of the total (Clarke, R.V. and Harris, 1992) and in 2002 and 2011 accounted for 30% and 20% respectively (Federal Bureau of Investigation, 2011a). Thus, places where a high proportion of youths live or where that population is concentrated due to activities provided for youth may experience a greater number of vehicle thefts. Findings by Roberts and Block (2012) have revealed that there is a positive association between temporary MVT rates (i.e. joyriding) and the percentage of young males in the population, but not with permanent MVTs (e.g. cars stolen and not recovered).

However, there is a contradiction in the findings on the relationship between MVT and the size of the youth population. Copes (1999) found that places with a high percentage of young males tend to experience low MVT rates (this study was based in a southern U.S. parish). Copes (1999) explains this result as being due to the fewer opportunities for MVT to occur in areas with a high proportion of young male population because of having only a few cars within these areas. This finding seems somewhat inconsistent with the findings of Hannon and DeFronzo (1998) study, which did not find any significant effect of the percentage of the population between the ages of 16 and 24 on MVT rates in large metropolitan counties in the U.S. In contrast to both studies, Andresen (2006b) study investigated MVT in Vancouver, Canada and found that MVT was significantly positively correlated with a young (male) population. This contradictory findings are more likely due to co-linearity with other variables and dependent on, for example, socioeconomic status.

In themselves young people may be less likely to have cars, but more likely to be offenders, and the balance is likely to rest on nuanced experiences of poverty. However, there are other issues where contradictions could reside. Recording issues or subsampling may have an effect. MVT can generally be divided into temporary MVT ("joyriding" theft for fun or travel) or permanent (theft for sale) thefts, and in some cases these are archived differently. Roberts and Block (2012) and Tremblay et al. (1994) highlight that offenders who commit temporary MVT tend to target available vehicles that are easy to steal and located not far from where the offenders live. This matches the profile of younger criminals discussed by Eck and Weisburd (1995), who suggest that criminals in their early years may tend to commit crimes near to their own residence, with this trend reversing for older criminals. Permanent MVT offenders certainly tend to be older adults and more professional at choosing their targets (Roberts and Block, 2012). Sample biases by crime type in MVT datasets will therefore align with age biases, with crimes by the more experienced being biased out of such datasets. A further explanation for contradictions in determining the effect of the number of local young people is that their influence may move and change with time. For example, the link between youth and crime may be notable in the places where young people live during sleeping hours, when young people stay home, whereas during the daytime and evening the links are more likely to be seen in places where young people are attracted.

The occurrence of MVT is not usually random but is concentrated in specific places (Fleming et al., 1994; Harlow, 1988). These locations can be associated with certain socio-economic characteristics (Eck and Weisburd, 1995). Socio-economic factors have been thoroughly examined in terms of how they relate to routine activities components: potential offenders, suitable targets and absent or incapable guardians. Therefore, in this study those factors will be reviewed in order to explain the occurrences of MVTs grounded upon the three components of routine activity theory.

Poverty is often found to be associated with the abundance of offenders. For example, Hannon and DeFronzo (1998) have found that MVT rates are significantly positively correlated with the percentage of poor families who were headed by females in the U.S. This suggests some corroborative evidence that areas with a high level of poverty can generate potential MVT offenders. In this vein, Copes (1999) used the proportion of poor people within neighbourhoods as an indicator for potential offenders for MVT under routine activity theory to investigate variations in MVT rates in a southern parish (county) in the US. He found that MVT rates were positively correlated with the percentages of poor people in neighbourhoods. This is in agreement with the findings of Messner and Blau (1987), who adapted routine activity theory to explain a number of types of crime using various socio-demographic characteristics of areas in the U.S. They found a significant positive relationship between MVT rates and poverty levels within the studied areas. Poorer areas tend to have vehicles that are more likely to be parked on streets with low levels of both surveillance and security systems. In a similar manner, Clarke, R.V. (1999) argue that vehicles in poor areas are more vulnerable to being stolen by potential offenders who live nearby since they tend to commit thefts close to their own homes. Another economic factor that can motivate offenders, and consequently influences MVT rates within neighbourhoods, is unemployment. Studies in the US (Roberts and Block, 2012; Hannon and DeFronzo, 1998) and in the UK (Sallybanks and Brown, 1999) found a positive association between unemployment and MVT rates.

4.2.1.2 Suitable Targets

The second element of RAT is the choice of a suitable target. In this study, the suitable target is a vehicle. Two of the most important characteristics of the suitability of the vehicle is its availability and accessibility by potential offenders. When one applies RAT to MVT, it is likely that the density of suitable targets at particular sites plays an important role in influencing MVT rates. Variables such as socio-demographics, road density, traffic density, population density and the number of car owners in a neighbourhood can be used to measure the density of suitable targets in a neighbourhood. Note, however, that the neighbourhoods where thefts occur are not closely correlated to those where the victims live.

A study by Sallybanks and Brown (1999) analysed the data sets from criminal statistics and the British Crime Survey to investigate vehicle crime trends in England and Wales in 1997. Their analysis of MVT identified that people characterised as single parent families, low income, house renters and aged between 16-24 were at higher risk of being victims of MVT than others. The findings of this study further support the idea of RAT since these targets are more prone to be targeted by potential offenders. For example, vehicles owned by people with these characteristics tend to have weak security systems, are parked in public places, i.e. not in a secure car parking area, and are close to potential offenders who live nearby. A further measure for suitable targets is the density of roads within neighbourhoods. The evidence of the effect of road density on MVT rates can be clearly seen in the study of Copes (1999) who used road density as an indication for suitable targets to explain MVT rates by applying routine activity theory. He found a positive relationship between the density of roads in neighbourhoods and the rates of MVT. However, one of the problems with aggregating all road types into a single type of road in order to measure the density of vehicles within neighbourhoods is that this can be misleading. This is because each type of road varies from every other in the amount/size of traffic volume and the presence of activities taking place along them; therefore, the density of vehicles varies across different types of roads in the area, throughout time. In this study, traffic data are unavailable; instead, the study will examine the influence of different types of roads on MVT occurrences throughout the day.

The third variable indicating the availability of suitable targets is the number of vehicles owned within a neighbourhood. One can expect that a greater number of cars owned in a neighbourhood would increase the MVT rates. However, contrary to this expectation, Copes (1999) study did not find a significant correlation between car density in a particular area and MVT when controlling for other variables in the U.S. In contrast to this finding, however, Roberts and Block (2012) found a negative relationship between vehicle density and permanent MVT rates but did not find any association between vehicle density and temporary MVT rates in the U.S. Roberts and Block (2012) and Copes (1999) studies both measured vehicle density by calculating the number of vehicles per square mile to indicate the availability of suitable targets for applying RAT in order to explain MVT. On the other hand, the finding of Roberts and Block (2012) study showed that the percentage of households without a vehicle was positively correlated with both temporary and permanent MVT rates, indicating that areas that have a high proportion of households with a lack of access to vehicles tend to experience higher MVT rates. Further support for this finding is evident in Clarke, R.V. and Harris (1992) findings, which suggested that the lower MVT rates in the U.S. are the result of the high levels of vehicle ownership. Therefore, this study will examine how the percentage of car ownership per household can serve to explain the availability of targets.

4.2.1.3 Absence of Capable Guardians

The third element of RAT is the absence of a capable guardian, which is required for a crime opportunity to occur. The level of guardians can be measured by types of vehicles and vehicles made. In addition, locations where cars are parked and the periods of time when they are parked can be used as measures for the levels of guardianships. This is evident in the case of neighbourhoods that are classified by certain characteristics that indicate the level of guardianship. A notable example of this is poor neighbourhoods that have a high number of vehicles with poor security levels, as they are more likely to be parked on the street or in driveways, due to a lack of secure garages. Research on MVT in the US has shown that the majority of cars are stolen from driveways near the owner's house (Ceccato et al., 2002; U.S. Department of Justice, 2000; Fleming et al., 1994). While, Copes (1999) study revealed that MVT rates were higher in neighbourhoods with a high percentage of poor people living in them. Taken together, these results suggest that there is an association between poor neighbourhoods and stolen vehicles from streets or driveways, that can be explained through the idea of low levels of guardianships in these areas.

A further factor that can influence the level of guardianship is the racial/ethnic heterogeneity. Walsh and Taylor (2007b) found that areas with high racial heterogeneity in a Midwestern city in the U.S. tend to experience high MVT rates. In line somewhat with this previous study, Sallybanks and Brown (1999) found that areas characterised as multi-ethnic tend to have high MVT rates in England and Wales. However, Rice and Smith (2002) did not find a significant influence of racial heterongenity on MVT rates in the Southeastern U.S. In contrast to earlier findings, Andresen (2006b) findings show that MVT rates were significantly and negatively correlated with levels of ethnic heterogeneity in census tracts in Vancouver, Canada. These previous contradictory results may be due to the different methods used in each study for measuring racial/ethnic heterogeneity within the studied areas. There are a variety of methods one might use for measuring ethnic heterogeneity and the effect of mixed social groups on community cohesion, such as the ratio of different ethnic groups (Walsh and Taylor, 2007a; Rice and Smith, 2002) or the percentage of immigrants to total population (Andresen, 2006b), and it is possible different metrics will reveal different underlying processes.

The studies mentioned above used ethnic/racial heterogeneity as a measure of social disorganisation. Hipp (2007), for example, suggested that high racial/ethnic heterogeneity contributes to reducing the levels of surveillance and guardianship in a community, consequently increasing crime rates within these areas. Equally, the ethnic diversity can decrease crime rates, implying either reduced offending or increased guardianship. However, it seems likely that, on its own, ethnicity is very unlikely to pick up the nuanced relationship between social, ethnic, and economic mixing and community cohesion in every circumstance, even if it is a good proxy in many.

A further characteristic of the neighbourhood that may indicate the level of capable guardianship is the percentage of housing tenure within areas. Studies by Flowers (2006a) and Weisel et al. (2006) revealed that MVT rates were higher in places where there are higher percentages of people living in rental houses. Clarke, R.V. and Mayhew (1994) highlighted that people who rent accommodation are at higher risk of being victims of MVT. One possible explanations for these findings may be that rental houses are more likely to have low or no secure car parking and hence vehicles are more easily accessed by potential offenders (Weisel et al., 2006). A further variable that affects the number of capable guardians is the population density in a neighbourhood. It is expected that an increase in population density will indicate an increase in the level of capable guardians in neighbourhoods based on the RAT hypothesis that “passer-by” could work as capable guardians to prevent crime (Felson, 1986). However, Copes (1999) used this variable to represent capable guardianships, so it was hypothesised that an increase in population density in area could consequently reduce MVT rates. Contrary to expectations, his study found that areas with a high density of population tend to experience high MVT rates. In this study, population density will be examined to measure the element of capable guardians based on the premises of the RAT. Similarly, Andresen (2006b) used this variable to measure guardianship, and found no significant effect on MVT rates in Canada.

Another socioeconomic characteristic of neighbourhoods that can influence MVT rates is the household income. Hannon and DeFronzo (1998) found that the average income variable was significantly and positively correlated with MVT rates for a sample of large metropolitan counties in the U.S. They explained that this finding could be the result of the high availability of suitable targets in areas with higher incomes. This seems in agreement with a principle hypothesis of RAT, which states that areas with relatively higher household incomes will experience higher property crime rates due to the availability of suitable targets (Hipp, 2007). However, a high family income might also be associated with higher values of the cars that have superior security systems, hence increasing the level of guardianship (Roberts and Block, 2012). Consequently, it might be expected that higher household incomes will have a negative association with MVT rates. This is a finding that has been reported in a number of studies (Roberts and Block, 2012; Walsh and Taylor, 2007a; Kennedy and Forde, 1990; Harlow, 1988).

Time is a critical factor in explaining RAT as it plays a crucial role in shaping activity patterns for people within a physical space. Peoples' activities during working days may differ completely from those during their holidays (Brantingham, P.J. and Brantingham, 2008). When the activities of both motivated criminals and potential victims intersect within their awareness space at certain times, then crime opportunities occur (Brantingham, P.J. and Brantingham, 2008). Therefore, MVT tends to be higher across neighbourhoods that have facilities which attract people at certain times of the day (Fujita, 2010; Rengert, 1997). The level of guardianship increases during specific periods of time and decreases at other times. This is evident in the evening period when night falls, which may reduce the level of guardianship. A number of studies on MVT (McCormick et al., 2007; Weisel et al., 2006; Mirrlees-Black et al., 1996; Clarke, R.V. and Mayhew, 1994; Fleming et al., 1994) have reported that the night period accounts for the highest number of MVTs. This further supports the idea of the effect of light on levels of guardianship in the findings of Clarke, R.V. (2002) who revealed that cars parked at night in areas with poor lighting are at greater risk of theft.

Overall, this section has reviewed the three key aspects of RAT: motivated offenders, availability of vehicles and incapable (or absent) guardians, and discussed how these elements can help explain occurrences of MVT. It is important to note that some variables introduced here under the perspective of RAT are often used to represent social disorganisation theory, such as poverty, racial heterogeneity and household income.

4.2.2 Crime Pattern Theory

The main concern of the crime pattern theory (CPT) is the built environments that work as crime attractors and generators (Weisburd et al., 2011; Andresen et al., 2010).

According to this theory, the built environment variables play an important role in explaining crime occurrences. Thus, by applying this theory to MVT, a number of studies have found two types of land use to have a high concentration of MVT and can be considered as crime generators: residential areas (McCormick et al., 2007; Weisel et al., 2006; U.S. Department of Justice, 2000; Fleming et al., 1994; Clarke, R.V. and Mayhew, 1994) and business areas (Fujita, 2010; Weisel et al., 2006; Henry and Bryan, 2000). There are specific locations within business districts that serve as crime attractors that could attract likely offenders and victims to come to these places. By way of illustration, several variables of business facilities are more vulnerable to having greater concentrations of MVT than other types of facilities, such as car dealerships (Weisel et al., 2006; Saville and Murdie, 1988), auto repair shops (Weisel et al., 2006) and bars, nightclubs, theatres, restaurants and blocks with high schools (Fujita, 2010).

Weisel et al. (2006) found that car dealerships and rental agencies exhibited a high frequency of MVTs amongst business locations in very rural areas in the U.S. On the other hand, the recent Canadian statistics (2007) on motor vehicle theft showed that car dealerships and car rental agencies had a very low percentage of motor vehicle theft incidents, accounting for only 1% of all auto thefts in Canada (Dauvergne, 2008). This rather contradictory result may be due to the type of area studied. The Weisel et al. analysis was conducted in very rural areas in the U.S which often have lower MVT rates compared to urban areas (Clarke, R.V., 2002; Sallybanks and Brown, 1999). It also suggested that business areas exhibited the highest MVT rates, which is in contrast to a wide range of contradictory research that reported residential areas to have the highest MVT rates. Several studies (McCormick et al., 2007; Weisel et al., 2006; U.S. Department of Justice, 2000; Fleming et al., 1994; Clarke, R.V. and Mayhew, 1994) have found that the highest frequency of MVT incidents occurred near the home of the vehicle’s owner.

Certain locations of residential neighbourhoods are more prone to have more MVTs than others. Previous research findings on investigating the geography of MVT have revealed that there is a higher likelihood for people who live in certain types of houses to be victims of car theft, such as terraced houses in England and Wales (Clarke, R.V. and Mayhew, 1994), flats in Sweden (Ceccato et al., 2002) and in England and Wales (Clarke, R.V. and Mayhew, 1994). These findings may corroborate the idea of CPT, which suggests crime generators and attractors. Residential areas that have a high percentage of terraced houses, flats and rental housing that provide opportunities for MVT to occur are considered as crime generators. While these types of houses which might have no garages and secure car parks attract potential offenders to steal vehicles, they tend to act as crime attractors.

Car parks are considered attractive places for vehicle theft. Fleming et al. (1994) indicated that large parking lots are the second most attractive location for auto thieves after driveways in British Columbia, Canada. This is in agreement with Rengert (1997), who found that "non-commercial parking lots" ranked as the second most popular location for MVT incidents after the streets near the home of cars owners in Philadelphia, USA. According to Wallace (2003), MVT incidents showed the highest frequency at parking lots (41% of all thefts), followed by streets (30%), in Canada in 2001. Kinney et al. (2008) investigated the concentration of MVT incidents in Burnaby in Canada in 2005, and they found that MVT was concentrated heavily in places where commercial and recreational activities took place. Overall, this emphasizes that car parks play an important role in attracting MVT.

Furthermore, some facilities located in residential neighbourhoods can increase the likelihood of motor vehicle theft because of the presence of particular characteristics that work as crime attractors. A good example of such facilities in residential districts is a community centre that might have a large car park with a low level of surveillance and high schools that have very young people. Fujita (2010) and Lu (2006) indicated that blocks with a large number of high schools are more vulnerable to having high MVT rates. This may match those revealed in a number of studies (Roberts and Block, 2012; Federal Bureau of Investigation, 2011a; Clarke, R.V. and Harris, 1992; McCaghy et al., 1977), that young males have been found to account for the majority of MVT. Additionally, those young males are at greater risk of being victims of MVT (Sallybanks and Brown, 1999). Hence, areas with a large proportion of high schools are expected to have a positive relationship with MVT rates. However, in this study, the data on high schools are not available and could not be included within the data analysis.

Specific roads serve as paths and activity nodes based on the CPT due to their vital role as connections to certain facilities that have some socioeconomic activities at certain time periods in the day, week and year that might attract potential offenders and victims from different places. For example, some parts of major roads have been reported to have a higher frequency of MVT incidents than other parts as a result of the presence of specific characteristics; for instance, it is easier to enter and access from different locations (Suresh and Tewksbury, 2013; Lu, 2006), and also those roads may have certain activities taking place along them (Lu, 2006). Matthews et al. (2010) found that freeways contributed to an increase in opportunities for MVT taking place in Seattle in the US.

It is also worth noting that there is somehow an overlap between both of the theories, RAT and CPT, from different aspects. This overlap could be attributed to the fact that crime pattern theory as introduced by Brantingham, P.J. and Brantingham (1993) was derived by combining some aspects of the theories that have already been proposed, such as RAT (Cohen and Felson, 1979), rational choice theory (Cornish and Clarke, 1987; Clarke, R.V. and Cornish, 1985).

Overall, this Section 4.2 has critically reviewed the existing Western MVT studies according to the core concepts of RAT and CPT. From this review, it is clear that there are few studies that have explicitly used the theoretical framework of RAT and CPT. Furthermore, these existing studies have emphasised the role of a wide range of factors in influencing occurrences of MVT. However, a number of contradictory findings have arisen from these studies in determining the influence of explanatory factors on MVT.

As we have obtained an understanding of how MVT has been studied in the West using the core theories of RAT and CPT, the following section will critically evaluate how RAT and CPT can be applied to explain MVT in SA.

4.3 How Might Differences Between Two Environments Influence the Applicability of Routine Activity and Crime Pattern Theories?

RAT and CPT were formulated and developed within a Western context, which is substantially different from the SA context, as previously discussed in Chapter 2 and 3. Therefore, it is important to determine if there are theoretical issues and considerations that should be taken into account when applying these theories to the Saudi context. This will help in guiding the analysis of MVT in Riyadh, SA, under the themes of these theories.

Empirical tests relating to RAT and CPT tend to focus on burglary and robbery in the US and Canada. They utilise aggregate socio-demographic datasets to examine the risks associated with a given crime. Such studies generally do well in the West, where the theories were generated, but can the theories be so easily converted to socio-demographic aggregates in other cultures?

It seems likely that the crimes at the centre of such theories may not be universally important. Each crime differs from another in the nature of the offence (Cornish and Clarke, 2008), the type of victim/target, the modus operandi, the characteristics of place in which the crime occurred, and the consequences of crime, etc. Furthermore, there are variations in the spatial distribution of the patterns for each type of crime, and, thus, spatial relationships are different for each type of crime (Eck et al., 2005). Socio-economic and demographic factors may influence the occurrence of burglary, but they may be less key in, for example, crimes against religion, where protest and individual psychology are likely to be more critical.

The Saudi Arabian context differs substantially from the Western context in terms of individual behaviour, demographics, culture, society and climate (see Chapter 3). It would therefore be unsurprising if the crime rates and types of crimes committed also varied substantially from the Western experience. RAT and CPT were originally developed within a specific cultural, socio-economic, physical and legal environment, and challenges are likely to arise when they are applied outside of the originating context.

4.3.1 Routine Activity Theory

Routine activity theory (RAT) argues that high levels of property crime, for example, are the result of certain social and economic conditions because of the opportunities those conditions create for crime. According to Cohen and Felson (1979), factors that can contribute to high levels of property crime include single adults living alone, females participating in the labour force, and a small household size, all of which results in the absence of capable guardians living in these homes during the day. These circumstances can contribute towards higher levels of residential burglaries being carried out against these households. These conditions are somewhat less applicable in the Saudi Arabian context, because in SA the average family size is larger, the percentage of females in the labour force only 13.2% in 2011 (The World Bank, 2016), and only 11% of Saudi females who were married participated in the labour force in 2009 (Central Department of Statistics and Information, 2009). This does not just have an effect on the number of capable guardians within a home, but also around it. Felson and Clarke (1998) and Felson (1986) pointed out that capable guardians are likely to be persons such as housewives, but also neighbours. Taking this context altogether, these conditions mean there are more capable guardians present in Saudi Arabian households during the day.

To a degree, the low rates of burglary in SA fit this RAT picture. However, what is seen in SA instead is a displacement of crime type, to MVT, but in ways that run contrary to RAT. Under standard RAT, we would expect car thefts to be low, because there are more guardians around in residential areas during the day, and work areas have high ambient populations during working hours. If we examined the system through the lens of standard RAT variables, we would expect MVT to be low. However, this would be to ignore two aspects of MVT. The first is the high mobility of the target. We argue that the element of capable guardians is difficult to measure for MVT using demographic variables. The difficulty of representing this element of MVT can be seen in previous studies. For example, published studies on the effect of population density are not consistent. Andresen (2006b) and (Copes, 1999) both explored capable guardians, but Andresen (2006b) found no significant effect, while Copes (1999) found a positive effect contrary to his expectations. The second is the relative risk associated with guardians.

Given that during burglary in SA there is a high risk of being interrupted by a guardian in a complex and unfamiliar space (the victim's home), crime is displaced into MVT. In MVT, street areas that appear statistically to be of high guardianship often lack the necessary quick access and easy oversight associated with guardianship in the West, and the environment is one that is more familiar and open. The latter lowers the risk for offenders caught in the act, and, indeed, this is seen in the fact that many MVTs in SA are perpetrated in places such as petrol stations and shops, where people often leave their keys in the ignition while paying. According to Public Security (2016), leaving vehicles unattended while the engine is running is considered the main factor contributing to vehicle theft in SA. These are high guardianship / high interruption rate, but low risk of capture / easy opportunity areas. Furthermore, as indicated, residents in the West are expected to play a role in protecting the vehicles parked outside their homes, since the design of houses in the West allows for occupants to observe outsiders and their surroundings, which makes potential offenders uneasy.

This element of self-protection is a core aspect of Crime Prevention Through Environmental Design (CPTED) (Cozens et al., 2005) and the Opportunity, Target, Risk, Effort, and Payoff (OTREP) framework proposed by (Kapland et al., 1978). Both approaches emphasise how the owner of any place being able to see their surroundings works as natural surveillance, which can contribute to reducing the opportunity for crime in the surrounding area. This can incorporate the role of routine activity theory, whereby occupants of houses such as housewives serve as capable guardians (Felson, 1986). In SA, however, there are often high walls surrounding houses which means that homeowners are unable to see the street areas (see Figure 3-8 in Chapter 3). Thus, potential car thieves in SA may have a lower level of risk, as espoused by CPTED (Cozens et al., 2005) and OTREP (Kapland et al., 1978). Therefore, occupants of houses in SA such as housewives are *unable* to play a role as capable guardians in preventing vehicle theft.

Little consideration has been given by both RAT and CPT to the setting of MVT occurrences, and few studies have attempted to contextualise MVT within the theoretical frameworks developed in environmental criminology. We could attribute this to the lower proportion of MVT compared to other property crimes in the West. According to Federal Bureau of Investigation (2012b) figures, in 2012 in the US larceny theft and burglary accounted for the highest rates (68.5% and 23% respectively) of all property crime, whereas MVT only accounted for 8% of property crimes. The lower home guardianship in the West, along with the shrinking of valuable goods to a portable size since the 1960s, favours burglary. In contrast, MVT targets have remained difficult to move and dispose of, and since the 1980s they have increasingly contained sophisticated security devices (Farrell et al., 2011a; Webb, 1994; Brantingham, P.J. and Brantingham, 1993; Cohen et al., 1980). In the US, therefore, there has been a substantial reduction in MVT rates since the mid 1960s (Webb, 1994) in comparison to property crimes such as burglary (Cohen et al., 1980) – although it is worth highlighting that both have reduced (Van Dijk et al., 2012).

In addition to the spatiality of crime, the temporality of offences is culturally determined. Different community activities practised by different cultures will have an influence on the routine activities of different peoples. In turn, these activities will influence patterns of crime events that occur at different periods of the day, week and month. Both RAT and CPT suggest that there is a concentration of burglaries during the daytime when people go to work, and when guardians are not present at home. Both theories look at the role of work patterns, time of day, and crime occurrence. As discussed, Cohen and Felson (1979) argue that burglaries have increased with the proportion of married women entering the workforce and the number of people travelling to work generally. Therefore, studies of the patterns of crime in the West are generally predicated on the dichotomy between working and residential hours. However, two issues may limit the applicability of this argument in terms of actual temporal patterns of MVT in terms of routine activities of people in SA.

Firstly, even the West, MVT incidents are not generally centred on low-guardianship working-hour patterns like the occurrences of burglaries; a wide range of studies have shown that the highest number of MVT incidents occurred during the night (Flowers, 2006b; Weisel et al., 2006; Clarke, R.V., 2002) in the US, in the UK (Mirrlees-Black et al., 1996), Canada (Fleming et al., 1994) and Australia (Henry and Bryan, 2000). In SA, the dominance of MVT and the issues of guardianship make for a more complex crime distribution than in areas where burglary dominates. Secondly, many of the events that move communities within SA are not related to work. For example, people attend mosques at certain times of the day for prayers during the week, and for more substantial periods during Friday prayer. The chart of traffic volume (Figure 3-4 in Chapter 3) shows that there is high traffic volume during the evening (outside working hours) because people in SA tend to do their shopping at night to avoid the hot weather of the daytime. We would expect these activities to influence crime patterns and opportunities in SA in the same way that working and commuting patterns do in the West. Nevertheless, applying RAT to alternative cultural settings highlights many of its difficulties, both in terms of theoretical applicability and practical use given the aggregate socio-demographic statistics generally collected by authorities. Most formal datasets are associated with residences, which is problematic when trying to understand the risk to movable objects and the risk associated with moving offenders, victims, and guardians.

This section has discussed the challenges that could limit the applicability of RAT to explain MVT in SA, Riyadh. Several factors have been highlighted – for example, the nature of MVT based on a movable object, the architecture of houses in SA and the fact that RAT, when it was proposed, considered the role of work patterns. The discussed factors in this section will be examined in the empirical work of this thesis.

4.3.2 Crime Pattern Theory

Crime pattern theory (CPT) tries to explain how the opportunities available to the offender can vary over space and time. The readiness is based on the characteristics of the backcloth, which includes legal systems, environments, and potential offenders' and victims' cultural, socio-economic, and demographic traits (Brantingham, P.J. and Brantingham, 1993). For example, CPT might consider the role of drinking alcohol as an influential factor on the readiness of offenders to commit crime, but also, more specifically, as a behaviour embedded in space – the locations of alcohol drinking becoming criminogenic areas. The theory highlights features of the built environment, such as pathways, wine bars, pubs, train stations and bus stops that work as nodes of concentration for crime. These are culturally dependent, and need determining separately for each culture. SA has very different built environment from that in Western countries. For example, it has no bars, train stations or bus systems working inside of its cities, and drinking alcohol is illegal. In addition, due to the desert climate conditions in SA, no paths are used for cycling or walking during the normal commute to work. Thus, the main means of transport in the country is motor vehicles. Cultural differences and differences in the built environment between SA and Western countries will clearly, therefore, result in different patterns of criminogenic nodes and opportunities.

The different criminogenic patterns can be clearly seen in the journey taken to commit MVT. Motor vehicles are the main form of transport in SA, and consequently these vehicles are expected to be used by car thieves when travelling to commit vehicle theft. This will therefore affect the distance that offenders travel and also the time at which MVT offences are committed. Consequently, MVT in residential areas is not expected to be particularly common during working hours, as vehicles are taken to work. MVT will also be less common during evening times when people use vehicles to do activities, as can be seen from the traffic data (Figure 3-4 in Chapter 3). Thus, it is expected that, in SA, vehicle thefts, which occur near victims' homes, are most likely to be limited to occurring during sleeping hours as vehicles are parked outside residents' homes, and car thieves feel that they are less likely to be seen during these hours.

This view can be supported by the findings of Al Angari (2002), who conducted interviews with a large sample of cars thieves in SA. Al Angari (2002) found that vehicles stolen while parked outside victims' houses accounted for fewer thefts than vehicles stolen while left unattended on the street with the engine running. Similarly, Al-Shaheen (1996) interviewed juveniles who committed car theft in Jeddah and Riyadh and found that most juveniles reported that they targeted unlocked cars with the keys in the ignition. Thus, in SA, it is expected that MVT is concentrated in residential areas where vehicles are more likely to be left unattended with the engine running, for example, when car owners are paying for groceries or petrol. In SA, grocery stores and petrol stations are common on streets in many residential neighbourhoods(see Figure 3-9), and drivers in this desert climate frequently leave their vehicles running with the air conditioning on. The low concentration of vehicle thefts near the homes of car owners is in contrast to Western countries, where MVT tends to occur in residential areas near the homes of car owners at night-time (McCormick et al., 2007; Weisel et al., 2006; Mirrlees-Black et al., 1996; Clarke, R.V. and Mayhew, 1994; Fleming et al., 1994). This will be examined in the empirical work in Chapters 7 and 8 that attempt to more strongly evidence some of these assertions.

Age is also a key factor that influences criminal mobility. This is supported by the ideas of Eck and Weisburd (1995), who suggest that criminals in their early years may tend to commit crimes near their own residences, which might be the reverse for older criminals. The majority of the SA population are young, which is in contrast to the structure of populations in the US and UK (see Section 3.2.1 in Chapter 3). Consequently, patterns of MVT in SA could differ from the West for two reasons. Firstly, the young population of SA means offenders are, on average, more likely to commit MVT in places where they live, during dark hours when vehicles are parked outside with little surveillance. Secondly, offenders are more likely to commit vehicle theft in places where they are attracted to node activities.

Different characteristics that emerge in the context of crime are explored by David and Scott (1973). In their study they compare juvenile delinquency in two cities, one in the US and the other in Argentina. Both cities had similar socio-economic, demographic and climate characteristics, but were substantially different in their built environments. David and Scott (1973) found that each city is dominated by certain types of crimes, and these crimes differ from each other. They conclude that these differences have arisen because of differences in the built environment. However, SA is not only different from Western countries in terms of built environment, but, as discussed above, in its ethnic, climate, culture, socioeconomic and demographic conditions also.

To sum up, this section has critically discussed the applicability of RAT and CPT, which will be applied in this study. This discussion has revealed that there are several factors that make the core elements of the theories, to some extent, difficult when attempting to employ them to explain MVT in SA. For example, despite the high presence of capable guardians in houses in SA, such as a high proportion of housewives, this has no significant role in preventing MVT due to the architectural design of Saudi houses. As a further example, the reliance on vehicles for daily activities, with no footpaths established inside neighbourhoods, makes the spatial-temporal distribution of MVT in SA different from the West. Overall, this section has highlighted a number of variables that will be examined in the empirical analysis of this study.

4.4 Chapter Summary

This chapter has built an understanding of the spatial patterns of MVT using RAT and CPT. Section 4.2 first critically reviewed the MVT studies conducted in the West from the perspective of RAT and CPT. Little consideration has been given to the perspective of either RAT or CPT in the problem of MVT, and few MVT studies have utilised these theories. This review also revealed a number of contradictory results concerning the relationship between MVT and other factors. A notable example, the relationship between a young population and MVT rates has variously been reported to be positive (Roberts and Block, 2012) or negative (Copes, 1999) and to have no effect (Hannon and DeFronzo, 1998). One reason for these contradictory results is that the Western MVT studies conducted so far have tended to treat the factors influencing MVT as consistent throughout the day. However, vehicles move from place to place, so the influence of the characteristics of various places on MVT fluctuates throughout the day.

After this literature review on MVT studies in the West, Section 4.3 raised key questions about the ability of the factors represented in RAT and CPT to explain MVT in SA, particularly in Riyadh. For example, according to RAT, the low female labour force participation and high percentage of housewives in SA are expected to lead to the presence of capable guardians in houses. However, the architectural design of Saudi houses, such as walls surrounding houses (see Figure 3-8 in Chapter 3), could make their occupants unable to function as capable guardians protecting vehicles parked outside. This chapter concluded with a discussion of the applicability of CPT, highlighting how differences in Saudi and Western built environments might result in different patterns of criminogenic nodes and opportunities. For example, in SA, the majority of population is young, motor vehicles are the main mode for transportation, and victims tend to leave vehicles unattended. These factors can influence two important elements of the crime template: awareness of space and offenders' readiness to commit crime. Therefore, the spatial-temporal patterns of MVT are likely to be different in SA and the West.

Chapter 4 is the last chapter presenting the theoretical framework of this thesis. The following chapters discuss the empirical work using theoretical framework developed in RAT and CPT to explain MVT in Riyadh, taking into account the theoretical concerns raised about the applicability of these theories. Chapter 5 will discuss the data and methodology implemented in this empirical work.

Chapter 5

Data and Methodology

5.1 Introduction

This study has established its theoretical framework through a discussion of the key theoretical concepts for the spatial analysis of crime under the principle themes of RAT and CPT as outlined in Chapter 2. Furthermore, the spatial and statistical methods used to accomplish the previous understanding were also reviewed in Chapter 2. The characteristics of the Saudi context in which RAT and CPT are applied were presented in Chapter 3. The final chapter of theoretical work was Chapter 4, as the empirical studies on MVT in the West were critically reviewed under the environmental criminology approach. Moreover, the applicability of RAT and CPT to explain MVT were critically discussed in Chapter 4. Having developed this theoretical framework, the next step is to integrate it with the empirical study in order to understand the spatial patterns of MVT in Riyadh, SA. The first stage of the empirical study is to describe the data and methodology being employed, which is presented here in Chapter 5.

Chapter 5 begins by outlining the source of the data used in the MVT analysis, including how the data were collected. Detailed descriptions of the data types are provided in Section 5.2. Section 5.3 explains how the data were prepared for analysis. It explains the preparation of MVT for analysis in Section 5.3.2. The following Section 5.3.3 provides brief descriptions for each socioeconomic, demographic and land use variable in terms of its type, how it represents elements of the RAT and CPT and how it was prepared.

The next task for this chapter – (Section 5.4) – is to provide details on how the methods were implemented to analyse the prepared data. The methodology has been divided into two main parts: exploratory analysis methods and modelling techniques. Section 5.4.1 explains the choice of the utilized mapping technique and also describes the spatial point pattern test adapted for detecting significant differences between MVT occurrences throughout the day. The results from implementing these methods will be presented in Chapter 6. Section 5.4.2 explains the regression models implemented in this study to examine and predict MVT. The results for modelling MVT will be shown in Chapter 7.

5.2 Data Description

This section will explain the types of data that were collected for analysis. They include information on motor vehicle theft (MVT), socioeconomics, demographics, land use and geographic data in terms of their sources, date-coverage and geographical scales.

5.2.1 MVT Dataset

The source of the data for the MVT analysis is calls for police services (CPS), which represent actual MVTs that were reported as offences. The National Information Centre (NIC) in Saudi Arabia provided this MVT data. The length of the period was from 1 January 2012 to 31 December 2014, which is the most recent period for which the data were available. The study period was selected to be long enough to ensure that the seasonal variation was captured. Furthermore, this study is not expected to suffer from the issue of under reported crime since it has been found elsewhere that victims of vehicle theft are most likely to report the theft to the police (Vito and Maahs, 2015; Office for National Statistics, 2013a; Chaplin et al., 2011; Australian Institute of Criminology, 2003), and there is no reason to suspect this would be any different for SA.

In terms of crime data from CPS, this is the first time that this type of data has been used in the analysis of crime in SA. However, CPS have been widely used in a range of crime studies (Andresen and Linning, 2012; Andresen and Malleson, 2010; Andresen, 2006b; Braga, 2001; Sherman and Weisburd, 1995; Spelman, 1995; Sherman et al., 1989). Using MVT data that has been obtained from CPS has several advantages over police recorded MVT data. It provides a geographic coordinate reference for the location where the criminal incident occurred. As this study is carried out at the neighbourhood level of Riyadh so this will help in aggregating the MVT at the neighbourhood level, at which point the MVT data can be examined in relation to the census data. By way of illustration, the crime data for Riyadh that can be collected from the police department is only available based on police districts, but each police district consists of several neighbourhoods. Furthermore, data based on CPS have more criminal incidents than recorded by the police departments. For example, there may be stolen-vehicle incidents in which the vehicle is recovered within hours by the victims or the police, and these will not be reported by the police departments but may be included in the CPS, according to the NIC (2014).

However, the limitation of this type of data is that there is a chance that such calls may be false (e.g. calling for incidents that do not exist) or may generate errors, such as multiple reports for the same incidents. Therefore, these issues were taking into account by the NIC. First, the NIC excluded all false data and included only incidents with complete details of the incidents with a unique Identification Number.

The obtained MVT data contains the following information:

- Date and time of occurrence
- Location of incident (geographic coordinate system)
- Description of location

5.2.2 Socioeconomic and Demographic Data

The available census data (2016) for Riyadh at the neighbourhood level was just released officially in 2016 by the High Commission of the Development for Riyadh (HCDR). This recent census data provides an advantage in terms of the analysis in this study. A wide range of crime studies suffer from huge differences in time between the crime data and demographic data, which can lead to biased statistical results (Andresen, 2014). This is because the census data is not gathered every year in most countries but rather every ten years, such as in the UK (Swan, 2012) and in the US (Mather et al., 2009). In SA, the collection of census data is not consistent with certain periods but has been carried out, on average, every eight to ten years according to the development plans in Saudi Arabia as a developing country. Therefore, this gap in time in the collected data between the explanatory variables and the crimes can reach up to nine years. Thus, potential changes in neighbourhood characteristics during this period will not be considered in the analysis (Andresen, 2014).

The following list shows the available census data for Riyadh in 2016:

- Population
- Sex
- Nationality: Saudi/Non-Saudi
- Age Categories
- Marital Status

- Educational Status
- Employment
- Number of Cars per Household
- Average of Family Size
- Housing Tenure: (Rented/Owned/Occupied)
- House Type

These variables will be explained later based on their use in the analysis.

5.2.3 Environmental Features

The High Commission of the Development for Riyadh (HCDR) provided the physical features for Riyadh as GIS files for 2012. The following is a summary of the main GIS files:

- Districts
- Roads networks
- Physical characteristics (housing, street type, service locations for shopping and so on)

5.3 Data Preparation

This section explains how the data were prepared for the analysis, but it does not present the results as this will be done in Chapters 6 and 7. This section shows the boundaries of the studied area, then explains how the MVT data were prepared for analysis by calculating the MVT rates. The selected variables for examining MVT in Riyadh will then be outlined using the themes of RAT and CPT.

5.3.1 Boundaries of the Studied Area

The map below (Figure 5-1) shows the boundaries of the studied area, which includes 157 neighbourhoods. Areas that were very rural, not populated and located outside the developed areas were excluded from the analysis. In addition, the area in the middle of the city that is white in colour has been removed as it has no census data.

It is occupied by medical services, including hospitals.

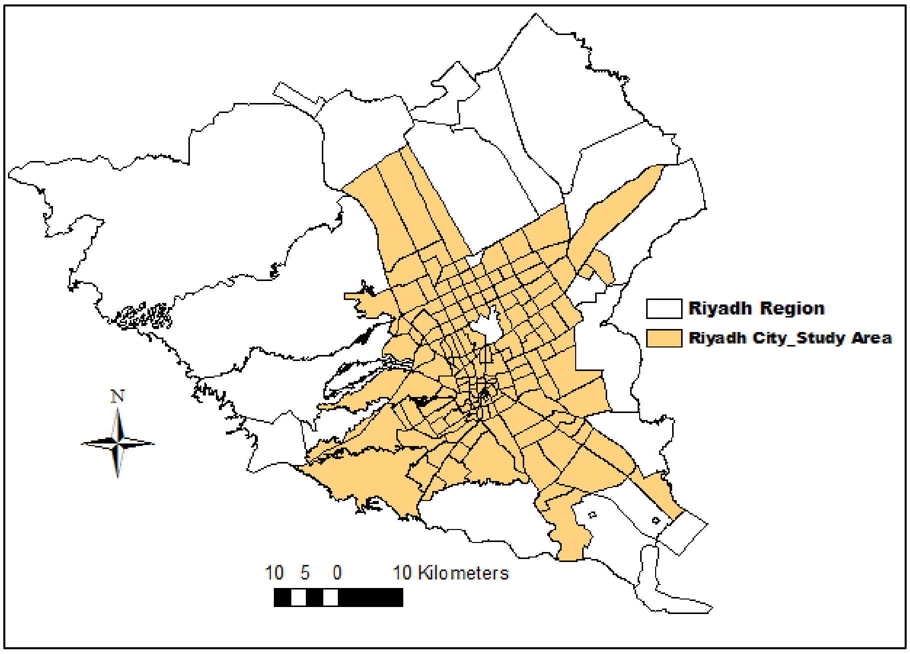


Figure 5-1: Boundaries of the study area (Riyadh city) and Riyadh region

5.3.2 MVT Measures

As the analysis applied in this study is largely quantitative, it is essential to define a measurement for crime. Two measuring methods for MVT were used in the analysis: MVT counts and MVT rates. They are described below. RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) emphasise the influence of the daily activities of potential offenders and victims on crime opportunities. This influence can vary over space and time as a result of these activities occurring at certain times. Consequently, the probability of MVT incidents during the day fluctuates due to variations in the degrees of influence for each factor that contributes to MVT in specific neighbourhoods. Therefore, it is important to examine each period of time separately in order to determine the effect of factors on MVT during each period. For the purpose of the analysis, MVT was categorised into four periods which roughly match the patterns of activity in SA: a sleeping period (night), a working and school period (morning), an after-work rest period (afternoon) and an activities period (evening). These periods are described as follows: Period One (night – 12 am to 6 am), Period Two (morning – 6 am to 12 pm), Period Three (afternoon – 12 pm to 6 pm) and Period Four (evening – 6 pm to 12 am). Table 5-1 below shows the descriptions of MVT incidents.

In terms of raw counts, we can see that the highest frequency of MVT incidents occurred during Period Four (6 pm to 12 am). The highest concentration of MVT occurrences in Riyadh, between 6 pm and 12 am, is partially consistent with a wide range of Western studies that have shown that the highest number of MVT incidents occurred during the night (Flowers, 2006b; Weisel et al., 2006; Clarke, R.V., 2002) in the US, in the UK (Mirrlees-Black et al., 1996), Canada (Fleming et al., 1994) and Australia (Henry and Bryan, 2000). However, the lowest frequency for MVT in Riyadh was during Period One (night), from 12 am to 6 pm, which is in contrast to these Western studies. This contrast will be investigated in Chapter 7 and discussed in Chapter 8. In addition, it is clear from the Table 5-1 that Period One and Two have a minimum of zero MVT incidents.

Table 5-1: Mean, median and standard deviations of MVT incidents in Riyadh

Periods	N. Neighbourhoods	Minimum	Maximum	Sum	Mean	Std. Deviation
MVT1	157	0	282	5643	35.94	44.165
MVT2	157	0	389	8682	55.30	67.229
MVT3	157	1	387	8686	55.32	63.493
MVT4	157	1	465	11284	71.87	84.091

Determining which method will be used to calculate crime *rates* is a critical step in crime analysis because rates of crime can vary significantly from low to high according to the denominator that is used. These differences in computing crime rates can lead to different results when analysing the same crime for the same areas (Malleson and Andresen, 2015; Felson and Boivin, 2015; Brantingham, P.L. and Brantingham, 1998; Beavon et al., 1994; Stipak, 1988). Therefore, it is important to identify the most accurate and relevant denominator for the rate of MVT.

Calculating rates of MVT can be achieved in different ways. First, the number of MVT incidents in a certain area can be divided by the capacity of car parking places for vehicles in this area (Andresen, 2014). This was an approach that was employed by Boggs (1965) in her seminal work on crime rates. The advantage of the use of this method is that it can give an expectation of the vehicle capacity of a neighbourhood even if these vehicles are not owned by households within the neighbourhood. However**,** there is a limitation to this method since it assumes that the maximum number of vehicles are present, with misleading results since the existence of a car park does not mean that it will be full of vehicles parked at any time. The second denominator used for MVT rates is the size of population at a residential site. Despite this method taking into account the number of people who live in an area, not everyone in the area may have a vehicle; rates of vehicle ownership might vary substantially. In addition, some households have more than one vehicle and others have none. Thus, using population as a denominator is less appropriate.

A third method is to use the number of vehicles owned per households in every neighbourhood. Although this measure will accurately capture residential vehicle ownership, it does not account for the possibility that some vehicles in a neighbourhood might originally have come from other neighbourhoods, particularly in non-residential areas (i.e. commercial districts). However, this could have less effect on the MVT rates since the MVT have been found to most often occur in residential areas (Tonry, 2011; Higgins, N. et al., 2009; Jetmore, 2007; McCormick et al., 2007; Weisel et al., 2006; U.S. Department of Justice, 2000; Fleming et al., 1994; Clarke, R.V. and Mayhew, 1994; Harlow, 1988). Furthermore, there is strong support for the use of this measure in numerous similar MVT studies (Roberts and Block, 2012; Walsh and Taylor, 2007a; Copes, 1999; Devery, 1993) and therefore in the remainder of this work the MVT rate, r, for an area, i, will be calculated by dividing the number of MVT incidents that occurred between 2012 and 2014, c, by the number of vehicles for households, v, in area i and multiplying by 1000, so the result can be interpreted as the number of vehicle theft per 1,000 vehicle.

$$r_i = \frac{c_i}{v_i} \times 1000$$

As indicated, the MVT data were categorised into four periods. Accordingly, the rates of MVTs were calculated in the four periods.

5.3.3 Census Data

This section attempts to explain the selected explanatory variables and describe how they were prepared for the analysis on the basis of the routine activity theory (RAT) and crime pattern theory (CPT).

The study is not the first of its kind in terms of using census data to test environmental criminology theories. A wide range of criminology studies have been undertaken using the environmental criminology approach with independent variables taken from census data (Roberts and Block, 2012; Cahill and Mulligan, 2007; Andresen, 2006a; Andresen, 2006b; Weisel et al., 2006; Rice and Smith, 2002; Copes, 1999; Messner and Blau, 1987). The independent variables in this project represent the socioeconomic, demographic and physical characteristics taken from the census in the neighbourhoods. In summary, these variables, which were discussed in Chapters 3 and 4 and represent the themes of theories, are outlined in the following section.

5.3.3.1 Variables of the RAT

The discussion of RAT provided in Chapter 2 and the empirical studies of MVT described in Chapter 4 revealed a wide range of factors that were found to influence MVT occurrences. Therefore, the following variables were selected to examine the elements of RAT.

- **Percentage of Males Aged 15-24**
  In summary, males aged between 15 and 24 were selected to represent the potential motivated offenders based on the findings of the literature reviewed. The young population constitutes the highest proportion of those arrested for committing MVT in the US (Federal Bureau of Investigation, 2011a; Clarke, R.V. and Harris, 1992) and in the SA (Al-Qahtani, 2008; Alwelaie, 1993). In this data, males aged between 15 and 24 comprised about 20% of the population in the neighbourhoods in Riyadh (see Table 5-2). SA generally has a much younger demographic than the US or UK – the proportion of 15-24 year olds in the UK is only 12.1 % of population in 2016 (CIA, 2016).

- **Poverty**
  Areas that have been classified as poor are more likely to have a higher proportion of motivated offenders than other areas (Clarke, R.V., 1999; Copes, 1999; Messner and Blau, 1987). Therefore, poverty was used to measure motivated offenders. However, the poverty level at the neighbourhood level is not available so the unemployment rate and the percentage of people with low or no education qualifications (LNEQ) were used as proxy indicators. They can be described as follows:

  1. **Unemployment:** The obtained census data provides information on the percentages of unemployed men and women among those who were

available and eligible to work in each neighbourhood (see Table 5-2 below for the description). It can be seen from Table 5-2 that the highest percentage of unemployed men is 16%. The average unemployment for the studied areas was very low (2%).

2. **Percentage of People with Low or no Education Qualifications (LNEQ)**
   The LNEQ was selected to indicate poverty because people with low levels of education are more likely to have low-income households, and consequently they have a higher probability of living in a poor area. People with low qualifications included those with intermediate educational qualifications or lower. The low qualification was identified based on the compulsory educational age in SA of 15, which has been applied since 2004 so the minimum level of education lasts until this intermediate education (age of fifteen).

- **Percentage of Households with no Vehicles (HNV)**
  The review of the literature indicates that a lack of access to vehicles can lead to increased motivation to commit vehicle theft (Robert and Block, 2012). Thus, the percentage of HNV is expected to represent motivated offenders. From Table 5-2 below, the average for the percentage of HNV in the study area was nearly 11% (Table 5-2).

- **Percentage of Students**
  This variable indicates the percentage of people above the age of 15 who were classified as students. Students have been found to more likely than the average person to commit MVT (Al-Qahtani, 2008; Al-Otaibi, 2002; Al-Shaheen, 1996; Fleming et al., 1994). Therefore, the percentage of students in neighbourhoods represents motivated offenders. In the study area, the average percentage of students comprised about 20% of the population (Table 5-2).

- **Percentage of Non-Saudi Males**
  This variable represents the percentage of non-Saudis who were male and aged 15 or over in every neighbourhood. The majority of non-Saudis came to SA to work. They constituted nearly 55% of the labour force in SA (Central Department of Statistics and Information, 2008b). This variable was selected for two reasons. First, since the majority of non-Saudis are workers, they tend to spend more time outside their homes. Consequently, they are more likely to be

vulnerable to vehicle theft based on the RAT. Thus, the first purpose of this variable is to represent household activity. The second purpose is based on the fact that the largest proportion of foreign workers are male; the areas predominated by these individuals tend to be poor due to low incomes. Thus, these poor areas are more likely to have vehicles with poor security levels, which could attract potential car thieves who live nearby. Consequently, areas with predominantly foreign workers are expected to be more vulnerable to high motor vehicle theft rates. Thus, this variable will be used to reflect household activity as well as areas with poor socioeconomic conditions. It is important to mention that the use of foreign workers as a predictor in this thesis does not suggest that overseas workers by nature have a higher tendency to commit crime than do Saudis.

As seen in Table 5-2, the average percentage of non-Saudi males was 37%.

- **Percentage of Employed Males**

The available census data provides information on employment status based on sex. Here, only the percentage of employed males was used because females are not allowed to drive in SA. This variable was chosen to test the hypothesis of RAT that participation in the labour force has increased the availability of targets (Cohen and Felson, 1979), in this case the number of vehicles.

- **Percentage of Renters**

In this research, the percentage of households that were renters in each neighbourhood in Riyadh was used to indicate suitable victims of MVT, as indicated in previous studies (Flowers, 2006a; Weisel et al., 2006; Sallybanks and Brown, 1999; Clarke, R.V. and Mayhew, 1994; Harlow, 1988). Table 5-2 illustrates that the average percentage of renters in the study areas was approximately 31%.

- **Percentage of Single People**

Single people were chosen to test the hypothesis of RAT (Cohen and Felson, 1979) that people who live alone are more likely to be victims of property crimes (as explained in Chapter 2). The average percentage of single people in the study area was about 41%.

- **Road Density**

The elements of RAT are mainly represented by socioeconomic and demographic variables (Andresen et al., 2010). However, the density of roads can also be used to indicate the availability of vehicles/targets (Copes, 1999). As discussed in Chapter 4, not all types of roads have the same level of traffic, and the presence of vehicles varies according to the type of road and the time of day. However, according to the HCDR (2012), the traffic volume for all types of roads exhibited the highest volumes during the evening between 6 pm and 12 am, whereas traffic data decreased to its lowest during Period One of 12 am to 6 am. In SA, according to the HCDR (2012), six types of road classifications in Riyadh. However, only the five main types of roads were selected to measure the availability of suitable targets, as the roads classified as ‘F’ (which are considered as lower-level local roads) were not available. It is important to indicate that these types of roads will also be used to reflect CPT themes as this theory is represented by the built environments (Andresen et al., 2010).

The types of roads are outlined as follows according to HCDR (2012):

1. Freeway roads are classified as A. A freeway road usually serves to connect cities and have high speed limits. In addition, they tend to have no traffic lights or stop signs, and there is no direct or immediate access to the adjacent developed areas and vice versa. Freeways tend to have the lowest density of facilities in comparison to other types of roads (High Commission for Development of Riyadh, 2012).

2. Major roads are classified as B, and these can be defined as roads that connect parts of the city to each other, such as those connecting the south side of the city to the north side.

3. Arterial roads are classified as C. The function of these roads is to carry the traffic of the city between the freeways and the collector roads. According to the data obtained from HCDR (2012), arterial roads have the highest density of facilities along them compared to other types of roads, with an average of 29.4 facilities per km.

4. Collector roads are classified as D, and these roads connect arterial roads to areas of development and residential properties, and they also deliver traffic from the local roads to the arterial roads.

5. Local roads are classified as E. This type of road has lower speed limits. These roads usually have direct and immediate access from all local points.

   The density, *d*, of each type of road in each neighbourhood, *i*, was calculated from the total length in km, *l*, for each type of road in a neighbourhood and the size of the area, *a*, in km^2.

$$d_i = \frac{l_i}{a_i}$$

- **Average Size of Family**

RAT emphasises the role of household size in influencing the opportunity for crime (Cohen and Felson, 1979). Therefore, the average family size at the neighbourhood level was selected to indicate the level of guardianship within households. It is expected that areas with a high average family size will tend to have low MVT rates and vice versa. From Table 5-2, the average family size in the study area was 5.6, which is close to the Saudi national average of about six people per family.

- **Percentage of Employed Females**

In this study, the percentage of employed women represents the absence of capable guardians. The RAT suggests that the employment of females contributes to the absence of capable guardians in houses (Cohen and Felson, 1979) and increases the number of suitable targets. As mentioned earlier, women are not allowed to drive in SA, so it is expected that this variable will only affect the level of guardianship. The average percentage of women who were employed in the study area was 21%.

- **Percentage of Housewives**

The percentage of housewives was used to indicate capable guardians based on the suggestion of the RAT. Felson (1986) suggested that 'housewives' represent capable guardians in houses. Thus, it is expected that areas with a high percentage of housewives will have lower MVT rates and vice versa. The descriptive Table 5-2 indicates that the average percentage of housewives in the study area was 44% of women.

- **Male Population Density**

  According to the hypothesis of the RAT, passers-by could act as capable guardians to prevent crime (Felson, 1986). Therefore, male population density was selected to measure the level of guardianship. In this study, male population density was calculated by dividing the total male population of an area by the total land area in km^2. The mean of the male population density in the study area was about 5124 people per km^2.

- **Diversity**

  The diversity variable can be defined as the diversity of the neighbourhood in terms of race and ethnicity. Diversity was used to measure the level of capable guardians. To clarify this, it is expected that high racial/ethnic heterogeneity contributes to reducing the levels of surveillance and guardianship because people who live in a cohesive community might act as capable guardians and consequently reduce the opportunities for crime to occur (Hipp, 2007). A more diverse community is generally assumed to lead to lower social cohesion (Laurence and Bentley, 2016) and a consequently higher crime rate (Hirschfield and Bowers, 1997). It is unclear to what extent this plays out in SA society, but is an important component of crime studies elsewhere, so is included as a potential explanatory variable. In this research, there was a lack of data on ethnic groups, and the only available information about race was with regard to Saudis and non-Saudis. Therefore, the diversity index was based on two categories—Saudis and non-Saudis—which were used as the measures for computing the diversity.

  The calculation of the diversity index was based on Brewer and Suchan (2001):

  1. Saudi proportion (SA) = the Saudi population in a neighbourhood divided by the total population in a given neighbourhood. Then, this proportion was squared.
  2. Non-Saudi proportion (Non-SA) = the Non-Saudi population in a neighbourhood divided by the total population in a given neighbourhood. Then, this proportion was squared.
  3. Then, the sum of the squares for SA and Non-SA were taken from 1.00.

The previous calculation can be represented in the following formula:

$$Diversity\ Index = 1 - \sum_{i=1}^{n} \left[\frac{x_i}{y}\right]^2$$

Where:

- x represents the population of ethnic group i of the neighbourhood.
- y represents the total population of the neighbourhood.
- n represents the number of ethnic groups in the population in the neighbourhood.

Table 5-2: Descriptive statistics of the RAT variables

Variables	N	Minimum	Maximum	Mean	Std. Deviation
%Renters	157	0.000	100.0	31.586	22.364
Average of family size	157	2.439	9.0	5.623	1.115
%Single	157	6.713	100.0	41.317	10.437
%LNEQ	157	13.791	100.0	44.835	16.639
%Unemployment	157	0.000	16.1	2.085	2.355
Diversity index	157	0.000	0.5	0.316	0.145
Male population density	157	2.830	31940.1	5124.361	6142.195
%HNV	157	0.000	72.7	11.284	14.808
%Age 15-24	157	0.000	80.0	20.551	8.858
%Housewives	157	0.000	100.0	44.039	14.727
%Employed females	157	0.000	64.2	21.158	14.037
%Employed males	157	37.807	100.0	69.497	14.509
%Students	157	0.000	53.0	20.617	10.736
%Non-SA males	157	1.444	100.0	37.210	26.807
Roads A density	157	0.000	3.6	0.350	0.439
Roads B density	157	0.000	4.6	0.885	0.858
Roads C density	157	0.000	4.4	0.376	0.585
Roads D density	157	0.000	4.3	1.118	0.869
Roads E density	157	0.000	32.3	10.081	6.961

5.3.3.2 Variables of the CPT

As discussed in Chapters 2 and 4, crime pattern theory (CPT) is represented by environmental features (Andresen et al., 2010). Hence, variables are outlined as follows:

- **Percentage of Residential Areas**

  The residential areas tend to have a high frequency of MVTs as explained in the reviewed literature (McCormick et al., 2007; Fleming et al., 1994). Thus, for the purpose of the analysis, this type of land use was selected as an MVT generator. It represents the proportion of residential areas in each neighbourhood in the areas studied versus the other types of land use in the same area.

- **Percentage of Apartment Buildings**

  People who live in terraces and flats have been reported to be more likely to be victims of MVT (Ceccato et al., 2002; Clarke, R.V. and Mayhew, 1994). In this study, the percentage of apartment buildings, as a type of residential building, in each neighbourhood is compared to the total residential buildings in the neighbourhood.

- **Density of Facilities**

  Facilities include any site that practises selling activities, such as restaurants, pharmacies and grocery stores, or any site that provides services, such as property offices and bank branches. Facilities are considered as crime attractors based on the CPT. The density of facilities was the number of facilities per km^2 in each neighbourhood.

- **Density of Car Facilities**

  Car facilities include any site that provides car services, such as car repair shops or shops that sell cars, car parts or accessories for cars. Car facilities are attractive places for car thieves. The density of car facilities is represented by the number of car facilities per 1000 available cars in a neighbourhood.

- **Car Parks**

  Car parks have been found to have a high frequency of MVTs (Wallace, 2003; Drugs and Crime Prevention Committee, 2002; Sallybanks and Brown, 1999). In this study, data on car parking capacity is not available. Therefore, for the analysis, the car-park variable is represented by the number of car parks per 1000 cars in a neighbourhood. Furthermore, car parks in this study include all types of car parks open for public use, regardless of whether they are paid or free of charge.

- **Percentage of Industrial Land Use**

Industrial areas are MVT generators due to the vehicles parked outside these sites for long hours, as found by Weisel et al. (2006) and Clarke, R.V. (1999). Thus, industrial areas were selected as predictors of MVT in Riyadh. Here, this variable is represented by the percentage of industrial land use in a neighbourhood.

- **Percentage of Recreational and Entertainment Land Use**

Recreational and entertainment locations include parks, museums, sports facilities and leisure centres. These sites, as mentioned in Chapter 4, attract people from different places at certain times. Hence, the percentage of recreational and entertainment locations in a neighbourhood was used as a variable to indicate attractive places for car thieves.

- **Percentage of Commercial Areas**

Commercial areas, which can also be called business areas, tend to have high MVT rates at different times (Kinney et al., 2008). Here, we should differentiate between the facilities mentioned above and commercial areas. In SA generally, facilities are distributed along the roads inside residential areas to serve surrounding residents, while commercial areas refer to lands that are specified only for commercial purposes, such as business companies, offices, malls and shopping centres. In this study, this variable is represented by the percentage of commercial land uses in a neighbourhood.

Table 5-3: Descriptive statistics for the CPT variables

Variables	N	Minimum	Maximum	Mean	Std. Deviation
%Recreational and entertainment	157	0	3.95	0.48	0.68
% Industrial land use	157	0	76.97	1.18	6.62
Car facilities density	157	0	883.00	17.13	90.48
Car parks	157	0	40.70	2.42	5.25
Facilities density	157	0.07	2491.71	200.3	319.81
%Residential areas	157	0	96.77	55.13	33.12
%Commercial areas	157	0	51.72	2.52	6.76
%Apartment buildings	157	0	100.00	21.54	28.15

To conclude, this section has described the necessary preparation process for the data used in the spatial analysis of MVT that occurred in Riyadh from 2012 to 2014. Since the MVT data was aggregated at the neighbourhood level, MVT rates were calculated in Section 5.3.2, representing the likelihood of MVT, which is the vehicle ownership in each area. Furthermore, 27 socioeconomic, demographic and physical variables have been described in relation to how they represent elements of RAT and CPT in Section 5.3.3. The following section will discuss how the data were analysed using several spatial and statistical analysis techniques to fulfil the thesis's objectives.

5.4 Methodology

The review of spatial and statistical analysis methods for crime patterns in Section 2.3 of Chapter 2 provided a guide for the implementation of these methods in this study. Therefore, the aim of the methodology section here is to explain the steps taken in order to understand the spatial patterns of MVT in Riyadh, SA. This section will begin by explaining the mapping technique used to visualise the spatial distribution of MVT across the study area during the four time periods (Section 5.4.1.1). Next, the use of the spatial point pattern test in this study to detect significant differences between spatial patterns of MVT throughout the day will be described. This first part of the analysis will examine the idea proposed by RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) that spatial crime patterns vary over space and time. The results from applying these methods will be presented in Chapter 6. Achieving this part of analysis will lead to the following modelling techniques.

Section 5.4.2 will describe the regression analysis techniques that are used to explain why MVT is more likely to occur in certain neighbourhoods and at particular time periods. The section will explain the adaption process of the ordinary least squares (OLS) regression method in order to identify the relationship between MVT rates and the explanatory variables for the RAT and CPT proposed in Section 5.3. Furthermore, the principal component analysis (PCA) will be discussed in terms of its uses for overcoming the multicollinearity issue and reducing the number of independent variables used in the analysis. Since the analysis of this study is based on spatial data, the consideration of spatial dependency is important for the results derived from the linear regression models. The use of global Moran's I as a measure for detecting spatial autocorrelation will be explained in Section 5.4.2.3. Next, the Section 5.4.2.4 will describe how a multinomial logistic regression model (ML) was used to determine the effect of the proposed factors on the probability of MVT occurrences in the four periods of the day. Finally, the methodology section will conclude with an explanation for the use of geographically weighted regression (GWR) in this study to overcome the issue of any existing spatial autocorrelation and to identify the relationships between the MVT rates and the factors representing the RAT and CPT at the local level – (spatial heterogeneity). The results from applying the regression methods will be presented in Chapter 7.

The flow chart in Figure 5-2 below summarises the process of the methods applied in this thesis:

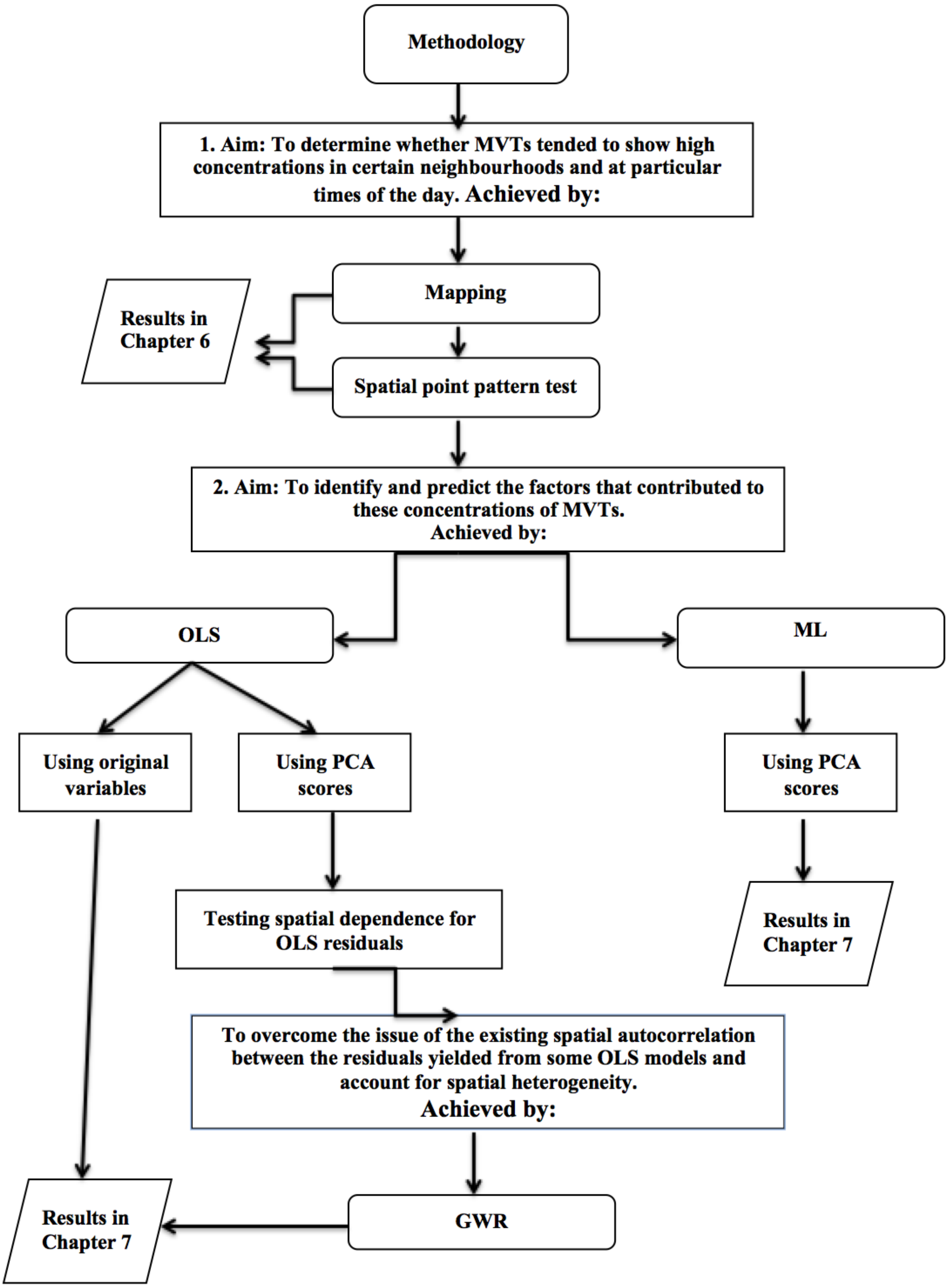


Figure 5-2: Flow chart summarises the process of the methods applied in this study

5.4.1 Exploratory Spatial Analysis Methods

The mapping technique and spatial point pattern test reviewed in Chapter 2 were adopted in this study to investigate whether MVT in Riyadh tended to show a high concentration of occurrences in certain neighbourhoods and during particular time periods of the day, as suggested by RAT and CPT. The following sections will describe how both methods were implemented to accomplish the aforementioned task, and then the results will be presented in Chapter 6.

5.4.1.1 MVT Mapping

This study is carried out at the micro-level, which here is the neighbourhood level. Therefore, thematic mapping method was used in this study to visualise the distribution of MVTs on maps for the four time periods. These maps can be compared against each other to identify whether the spatial patterns were different or similar, with high and low rates of MVTs. The thematic maps display crime events and rates on the map with shaded colours crossing the areas studied (Canter, 2000; Chainey and Ratcliffe, 2005). Shaded colours that present counts or rates of crime in different classes are produced by various techniques. The most common classification technique used in crime mapping is quantile classifications (Boba, 2005).

For this study, the quantile classification was chosen because it is relevant for the comparison of different maps in different datasets times series (GeoSWG, 2012) with different values (Boba, 2005). The idea of this method is that it splits an equal number of areas in each class based on the defined number of classes chosen by the user, from the lowest values in the first class to the highest values in the last class (Boba, 2005; Reno et al., 1999). For example, in this study, the quantile method allowed the comparison and identification of the highest and lowest 20% of the neighbourhoods when five classes were selected. This helps to determine whether the areas with the highest MVT rates during Period One were also the highest in MVT rates during Period Four and so on. The thematic maps were produced using the ArcGIS program will be shown in Chapter 6.

5.4.1.2 Spatial Point Pattern Test

The previously described mapping technique is useful for identifying hotspots of MVTs during each period. However, to identify significant changes or differences between the studied periods, the spatial point pattern test is suitable.

The RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011;

2008; 1993) suggest that crime opportunities vary over space and time due to the daily activities of potential offenders, victims and capable guardians. For this reason, as was mentioned in Section 5.3, the MVT occurrence was divided into four periods of the day. It is critical in the spatial analysis to detect significant differences between the spatial patterns of MVT throughout the day as these indicate that different factors generate the spatial patterns of MVT during each period. The spatial point pattern test developed by Andresen (2009) was used in this study to compare the MVT occurrences across the study area during the four time periods in order to detect statistically significant differences in the spatial patterns.

For this comparative analysis, the base dataset and test dataset were chosen based on the chronological order. For example, Period One (12 am to 6 am) was the base dataset and Period Two (6 am to 12 pm) was the test dataset, etc. The general working procedure for this test is described as follows (Andresen, 2009):

1. After determining the base dataset and the test dataset, the software counts the number of points for each area in the base dataset.
2. Next, 85% of the points that occurred in each area in the test dataset are selected randomly as a sample and counted as is done with base dataset.
3. The test software allows the user to identify the number of iterations for repeating the previous step for the test dataset. For this analysis, the option of 100 iterations was selected to determine the statistical differences and create the confidence interval .
4. The selected confidence interval for this study was 95%. The confidence interval is determined for each spatial unit in the study area by calculating the percentage of the points in each spatial unit of analysis of the sample of the test dataset.
5. Finally, the percentage of crimes counted in each area for the base dataset is compared to the generated confidence interval from the test dataset in each area. The results then show the significant differences between the spatial patterns of the two datasets at the global and local levels.

The test provides a global index that indicates the overall significance of differences between two data sets for the study region. The formula for calculating this Index of similarity, S, is as follows:

$$s = \frac{\sum_{i=1}^{n} s_i}{n}$$

Where:

- n represents the number of areas.
- i represents the areal unit.

The global index value falls between 0, which indicates no similarity, to 1, which indicates a perfect similarity (Andresen, 2009). However, the values may fall between 0 and 1, such as 0.5 and 0.2, so the threshold used is 0.8 and over indicates that the patterns for the two datasets are similar (Andresen, 2016), whereas when the values are very close to zero such as 0.3, this indicates that the patterns tend to be more different. Furthermore, the test determines if there is any significant differences between the two crime data sets over the different time periods in the neighbourhoods. The output of the test can be mapped to show areas that are significantly different (Local Index = +1, -1) or insignificantly different/similar (Local Index = 0) (Andresen, 2009). The results from implementing the spatial point pattern test will be presented in Chapter 6.

5.4.2 Regression Analysis

As stated in Chapter 2, the ultimate purpose of the spatial analysis of crime is to determine the factors that create the spatial patterns of crime clustered in certain neighbourhoods at particular times. In this study, the factors introduced in Section 5.3 under the themes of RAT and CPT were examined to see if there is a statistically significant association between them and MVT using regression analysis methods. This aims to achieve the core objective of this study in understanding the spatial patterns of MVT, Riyadh, SA. Thus, the relationships between the MVT rates for the four time periods during the day and the variables representing RAT, CPT, and the integration of the two theories, were identified by the OLS as described in Section 5.4.2.1. Regression models assume no high multicollinearity between the independent variables, so the PCA was implemented as explained in Section 5.4.2.2. Furthermore, the global Moran's I is described in Section 5.4.2.3 to detect spatial autocorrelation in residuals yielded from the OLS regression models. Next, to determine the effects of selected variables on the probability of MVT occurrences during the four time periods, multinomial logistic regression (ML) was conducted (Section 5.4.2.4). GWR is applied as a final model for MVT rates to improve the power of the OLS regression models in predicting MVT rates at the local level (Section 5.4.2.5). Thus, the following sections attempt to describe the process undertaken for modelling MVT and the results of these models are explained in Chapter 7.

5.4.2.1 OLS Regression Model

The ordinary least squares (OLS) method has been used by numerous studies for modelling MVT (Walsh and Taylor, 2007b; Cahill and Mulligan, 2007; Ceccato et al., 2002; Rice and Smith, 2002; Copes, 1999) as has been reviewed in Chapter 2, Section 2.3.2. Here in this study, the OLS was adapted to determine the factors that contributed to MVT rates during the four study periods. OLS can be applied to examine and predict crime occurrence at different locations and over different periods of time.

The simple formula for the regression model is (Pohlman and Leitner, 2003):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_n x_n + \varepsilon$$

Where, x are independent variables, and y, the dependent variable; $\boldsymbol{\beta_0}$ is the intercept of the true regression line. $\boldsymbol{\beta_1}$ is the slope of the true regression line and ε is the random error. ε incorporates the effects on y of all variables (factors) other than x in such a way that their net effect is zero on the average.

The regression analysis in this study was implemented through the Statistical Package for Social Science (SPSS). The SPSS was used for describing, summarizing, exploring relationships between variables, and interpreting data. In order to examine the relationships between MVT rates and variables representing RAT and CPT, the OLS regression method was applied, producing 20 OLS models to examine MVT utilising RAT (eight models), CPT (eight models) and their integration (four models). The outputs of these regressions are included in Appendix A. The main results of the OLS models including significant predictors for MVT, and statistical measures are presented in Chapter 7. Several assumptions were tested by implementing the OLS regression models described in the following subsections.

Testing for Normality

The multiple regressions assume that the dependent variables are normal distributions (Leech et al., 2005). To test this assumption, the value of skewness, as shown in Table 5-4, was used to determine whether any violation of the model assumption occurred. If the value of skewness falls between +3 and -3, this indicates a normal distribution for a dependent variable (Lewsey, 2006).

Table 5-4: Descriptive statistics for the MVT rates in the four time periods

Periods	N	Minimum	Maximum	Mean	Skewness	Std. Error
MVT1	157	0.00	89.65	5.02	5.89	0.194
MVT2	157	0.00	366.26	12.16	7.12	0.194
MVT3	157	0.19	447.65	11.50	9.30	0.194
MVT4	157	0.17	284.87	12.83	6.09	0.194

Table 5-4 above shows that the data for the MVT rates in the four time periods were not normal distributions; the skewness values range from 5.8 to 9.3, which indicates that they were highly positively skewed in Table 5-4. This is to be expected, crime rates are often not normally distributed; they are skewed (Wallace et al., 2006). To overcome the issue of the highly skewed data of the MVT rates during the periods, the data were transformed in order to reduce this skewness to an acceptable statistical level. However, as is shown in Table 5-4 above, the minimum values of MVT rates during Periods One and Two were zero. Specifically, there were two cases in Period One that returned a value of zero and one case in Period Two with the same value, so the log transformation for MVT rates will not work for these periods. Therefore, it is appropriate to add a value of one to the log transformation—“log (y+1)”—in order to overcome this error (Heck et al., 2013; Yaremko et al., 2013; Valiela, 2009).

It is clear from Table 5-5 that the MVT data have become more acceptable, although there was some skewness still; fortunately, the data now falls within usable limits (Leech et al., 2005).

Table 5-5: Descriptive statistics for the log of MVT rates

Periods	N	Minimum	Maximum	Mean	Skewness	Std. Error
MVT1	157	0	1.96	0.60	1.48	0.194
MVT2	157	0	2.56	0.75	1.42	0.194
MVT3	157	-0.72	2.65	0.64	0.85	0.194
MVT4	157	-0.76	2.45	0.75	0.60	0.194

Testing for Multicollinearity

The OLS regression assumes no or little multicollinearity between the independent variables (Pringle, 1981). To overcome this problem, two strategies were applied. First, the OLS regression models for the RAT and the CPT were run after excluding one of the variables with a correlation above 0.8 (see Correlation Matrix in Table 5-6). In addition, due to the effect of multicollinearity (Yoo et al., 2014), variables that changed their effects on MVT rates – for example, from a real positive prediction to a false negative prediction – were excluded to overcome this issue. This included the variables of male population density and housewives. The aim of this step was to explore the effect of the independent variables on predicting MVT rates. The second strategy was to perform a principle component analysis (PCA), which will be described in Section 5.4.2.2 to overcome the high multicollinearity between the independent variables and to reduce the number of independent variables used in examining both theories.

Running the OLS Regression Model

The OLS regression was run using the stepwise techniques for modelling MVT rates with variables relevant to RAT, CPT and an integration of both theories. The assumption that the independent variables should be statistically significant in predicting the MVT variable were met. The values of significance for these variables in all regression models were less than 0.05. In addition, the standardised coefficients for the beta were used to indicate the effect size of the variables.

Regression Model Diagnostic

The OLS regression function in SPSS provides statistics on the collinearity. The tolerance, which should be greater than 0.1, and the variance inflation factor (VIF) scores should be less than 10 (Landau and Everitt, 2004) were checked to see if they met the assumption for all regression models. The assumption of the multiple regression models that the independent variables are not highly correlated to one another was not violated. Partial regression plots were used to examine the correlation between the MVT rates and each independent variable after the influence of the other variables had been removed (see the Appendix A). In addition, the results of the OLS regression models were tested for independency between the observations. The values of the Durbin-Watson statistic were all between 1 and 3 for all models (see Chapter 7), which are in the acceptable range, and this indicates a lack of autocorrelation between the residual terms (Field, 2009).

Furthermore, the criterion of homoscedasticity for the variance of the residuals across the predicted values was tested and was met, as shown in the scatter plots (see the Appendix A), which illustrate the variance of the residuals. Furthermore, to test the assumption that the residuals are normally distributed, the normal P–P Plot of the regression standardized residual was used. The assumption was not violated, and the residuals for all regression models were distributed roughly close to the line of the expected values. Therefore, the final models are presented in Chapter 7 with independent variables with significance (all p-values <0.05), and there were no significant problems that statistically violated the assumptions of the traditional multiple regression models (see the graphs outlined in the Appendix A). However, as the spatial process is the main concern for the spatial data, the residuals yielded from the OLS regression models were checked for spatial autocorrelations using global Moran's I (see Section 5.4.2.3).

5.4.2.2 Principle Component Analysis (PCA)

The PCA was conducted to transform a number of independent variables that represent the RAT, CPT and the integration of both theories to fewer variables (a set of components), potentially representing hidden system components related to the collected (proxy) variables. In addition, it was also used to overcome the high multicollinearity in the independent variables as explained in the previous section. The extracted components are uncorrelated, but they correlated with the original variables and can explain most of the variance of the original variables (Jackson, 2005). The following general formula explains how the component is computed (O'Rourke and Hatcher, 2013):

$C^1 = b^{1,1} (X^1) + b^{1,2} (X^2) + ... b^{1,p}(X^p)$

Where:

C^1 = the subject's score on principal component 1 (the first component extracted)

$b^{1,p}$ = the regression coefficient (or weight) for observed variable p, as used in creating principal component 1

X^p = the subject's score "The variable value""- on observed variable p.

Running the PCA

In order to run the PCA, the correlations between the majority of independent variables should exhibit a value of correlation of 0.3 or higher (Tabachnick et al., 2001). Thus, by looking at the correlation matrix in Table 5-6 for the RAT, CPT and an integration of both theories, it can be seen that some variables were correlated with each other above 0.3, which suggests that the PCA can proceed. However, for the RAT variables, freeways (A) had a very weak correlation with all other variables, as the value of its correlation with the other variables was 0.1 or lower. This can result in loading freeways 'A' only in its own component. In this analysis, 'A' was not removed from the PCA in order to determine its significance in the regression analysis.

Table 5-6: The correlation matrix for all independent variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	1.00	0.04	-.166*	0.15	.184*	.225**	.394**	0.12	-0.09	-0.05	0.11	0.08	-0.12	0.03	-0.12	0.03	0.08	0.15	.324**	-0.09	-0.11	-0.05	-.214**	.279**	-0.11	-0.01	.231**
2	0.04	1.00	.267**	-0.05	.341**	.221**	-0.12	-.438**	.340**	.257**	-.280**	-.669**	.547**	-.526**	0.00	-.205**	-0.09	0.08	-0.07	-0.08	-.248**	-.214**	-.214**	-.266**	.247**	-.198*	-.253**
3	-.166*	.267**	1.00	.300**	0.14	-0.10	-.234**	-.286**	.628**	-0.02	-.407**	-.400**	.290**	-.191*	-0.05	-.161*	-0.04	0.02	-.173*	-.164*	-0.12	.169*	.203*	-.216**	0.04	-.160*	-.296**
4	0.15	-0.05	.300**	1.00	.218**	-.309**	.317**	.342**	0.00	-.485**	0.06	.319**	-.406**	.464**	-0.04	-0.03	.174*	-.182*	.188*	-.239**	-0.06	.247**	.158*	.283**	-.389**	-0.09	.357**
5	.184*	.341**	0.14	.218**	1.00	-0.02	0.02	-0.02	0.14	-.161*	0.00	-.318**	0.08	-.220**	0.04	-.158*	-0.02	-0.05	0.03	-0.11	-0.10	-0.02	-.200*	-0.07	0.13	-0.12	0.06
6	.225**	.221**	-0.10	-.309**	-0.02	1.00	-0.10	-.229**	-0.04	.428**	-0.07	-0.10	0.11	-.246**	0.00	0.02	-0.12	0.15	0.16	-0.06	-.236**	-0.11	-.256**	-0.13	.369**	0.12	-.211**
7	.394**	-0.12	-.234**	.317**	0.02	-0.10	1.00	.369**	-.223**	-.290**	.297**	.382**	-.372**	.470**	-0.02	.469**	.428**	0.06	.826**	-.186*	-0.13	-0.13	-0.15	.741**	-.164*	0.05	.714**
8	0.12	-.438**	-.286**	.342**	-0.02	-.229**	.369**	1.00	-.459**	-.308**	.309**	.624**	-.611**	.616**	0.06	.201*	.266**	-0.04	.219**	-0.03	.365**	0.10	0.13	.457**	-.418**	0.08	.570**
9	-0.09	.340**	.628**	0.00	0.14	-0.04	-.223**	-.459**	1.00	0.08	-.383**	-.536**	.581**	-.409**	0.04	-.216**	-0.13	-0.02	-.195*	-0.04	-0.11	-.181*	0.02	-.252**	0.14	-0.15	-.362**
10	-0.05	.257**	-0.02	-.485**	-.161*	.428**	-.290**	-.308**	0.08	1.00	-.534**	-.260**	.325**	-.392**	0.10	0.02	-.216**	.272**	-0.07	0.08	-0.15	-.182*	-.204*	-.313**	.391**	0.00	-.409**
11	0.11	-.280**	-.407**	0.06	0.00	-0.07	.297**	.309**	-.383**	-.534**	1.00	.308**	-.257**	.236**	-0.03	0.13	0.15	-0.07	0.15	0.10	-.207**	0.13	-0.13	.343**	-.216**	.169*	.375**
12	0.08	-.669**	-.400**	.319**	-.318**	-0.10	.382**	.624**	-.536**	-.260**	.308**	1.00	-.882**	.854**	0.03	.287**	.228**	-0.06	.235**	0.09	.242**	.185*	.198*	.396**	-.402**	.169*	.573**
13	-0.12	.547**	.290**	-.406**	0.08	0.11	-.372**	-.611**	.581**	.325**	-.257**	-.882**	1.00	-.822**	-0.01	-.200*	-.191*	0.06	-.243**	0.01	-.214**	-.271**	-.294**	-.386**	.358**	-0.14	-.550**
14	0.03	-.526**	-.191*	.464**	-.220**	-.246**	.470**	.616**	-.409**	-.392**	.236**	.854**	-.822**	1.00	0.05	.339**	.298**	-0.15	.302**	0.05	.252**	.197*	.285**	.456**	-.485**	.173*	.669**
15	-0.12	0.00	-0.05	-0.04	0.04	0.00	-0.02	0.06	0.04	0.10	-0.03	0.03	-0.01	0.05	1.00	-0.10	-0.08	0.03	-0.03	0.14	0.00	-0.09	-0.11	-0.11	0.13	0.06	0.03
16	0.03	-.205**	-.161*	-0.03	-.158*	0.02	.469**	.201*	-.216**	0.02	0.13	.287**	-.200*	.339**	-0.10	1.00	.262**	0.11	.500**	0.08	-0.14	-0.08	-0.11	.498**	-0.15	.202*	.452**
17	0.08	-0.09	-0.04	.174*	-0.02	-0.12	.428**	.266**	-0.13	-.216**	0.15	.228**	-.191*	.298**	-0.08	.262**	1.00	-0.06	.458**	0.04	-0.04	-0.04	0.05	.322**	-.183*	0.01	.424**
18	0.15	0.08	0.02	-.182*	-0.05	0.15	0.06	-0.04	-0.02	.272**	-0.07	-0.06	0.06	-0.15	0.03	0.11	-0.06	1.00	0.08	0.07	-0.15	-0.11	-.195*	0.06	.335**	0.02	-0.05
19	.324**	-0.07	-.173*	.188*	0.03	0.16	.826**	.219**	-.195*	-0.07	0.15	.235**	-.243**	.302**	-0.03	.500**	.458**	0.08	1.00	-.261**	-.229**	-0.12	-.250**	.692**	0.06	0.09	.535**
20	-0.09	-0.08	-.164*	-.239**	-0.11	-0.06	-.186*	-0.03	-0.04	0.08	0.10	0.09	0.01	0.05	0.14	0.08	0.04	0.07	-.261**	1.00	-0.08	-0.04	0.16	-0.15	-0.09	0.06	0.13
21	-0.11	-.248**	-0.12	-0.06	-0.10	-.236**	-0.13	.365**	-0.11	-0.15	-.207**	.242**	-.214**	.252**	0.00	-0.14	-0.04	-0.15	-.229**	-0.08	1.00	0.10	.342**	-0.08	-.189*	-0.06	0.05
22	-0.05	-.214**	.169*	.247**	-0.02	-0.11	-0.13	0.10	-.181*	-.182*	0.13	.185*	-.271**	.197*	-0.09	-0.08	-0.04	-0.11	-0.12	-0.04	0.10	1.00	.457**	0.08	-.233**	-0.03	-0.07
23	-.214**	-.214**	.203*	.158*	-.200*	-.256**	-0.15	0.13	0.02	-.204*	-0.13	.198*	-.294**	.285**	-0.11	-0.11	0.05	-.195*	-.250**	0.16	.342**	.457**	1.00	-0.03	-.392**	0.02	0.01
24	.279**	-.266**	-.216**	.283**	-0.07	-0.13	.741**	.457**	-.252**	-.313**	.343**	.396**	-.386**	.456**	-0.11	.498**	.322**	0.06	.692**	-0.15	-0.08	0.08	-0.03	1.00	-.320**	0.12	.630**
25	-0.11	.247**	0.04	-.389**	0.13	.369**	-.164*	-.418**	0.14	.391**	-.216**	-.402**	.358**	-.485**	0.13	-0.15	-.183*	.335**	0.06	-0.09	-.189*	-.233**	-.392**	-.320**	1.00	-0.15	-.406**
26	-0.01	-.198*	-.160*	-0.09	-0.12	0.12	0.05	0.08	-0.15	0.00	.169*	.169*	-0.14	.173*	0.06	.202*	0.01	0.02	0.09	0.06	-0.06	-0.03	0.02	0.12	-0.15	1.00	0.11
27	.231**	-.253**	-.296**	.357**	0.06	-.211**	.714**	.570**	-.362**	-.409**	.375**	.573**	-.550**	.669**	0.03	.452**	.424**	-0.05	.535**	0.13	0.05	-0.07	0.01	.630**	-.406**	0.11	1.00

Renters (1),Average of family size(2),Single(3),LNEQ(4),Unemployment(5),Diversity(6),Male population density,(7)HNV(8),Age_15_24(9),Employed females(10)Housewives(11),Employed males(12),Students(13),Non-SA males(14),Roads_A(15),Roads_B(16),Roads_C(17),Roads_D(18),Roads_E(19),Recreational and entertainment(20),Industrial land use(21),Car facilities(22),Car park(23),Facilities(24),Residential areas(25),Commercial areas(26),Apartment buildings(27).

Testing the Relevance of the PCA

The Kaiser-Meyer-Olkin (KMO) is a measure of sampling adequacy (MSA) that indicates the degree of collinearity between the variables for the three models separately: RAT, CPT and an integration of both theories. It has been suggested that the value of KMO should be greater than 0.7, and if it is lower than 0.5, PCA would not be appropriate (Leech et al., 2005). The values of the MSAs for the RAT variables, CPT variables and integration variables are 0.701, 0.635 and 0.718, respectively, and the Bartlett tests for all were significant ($P<0.05$), which suggests that there were some high correlations amongst the variables and that several common factors may be detected.

Interpretation of the PCA Results

The number of components that were extracted was based on the eigenvalues. The eigenvalue's orthogonal indicates how each extracted component can explain the total variance of the original variables (Wuensch, 2012). In this analysis, components with values of one or greater were retained as common criteria for the adequate factor (Leech et al., 2005). The extracted components are displayed in Tables (5-7), (5-8) and (5-9), which show the components for the variables representing the RAT, CPT and the integrated version. These extracted components explained the following total variances of the original data: 71.6% for the RAT, 59.1% for CPT and 71% for the integrated variables. Tables 5-7, 5-8 and 5-9 indicate that the first components for the PCAs represented the majority of the variation in the data, accounting for about 22% of the variance after rotations for RAT, 23% for CPT and 18% for the integrated version.

Table 5-7: Total variance explained by the RAT components

Components	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	4.14	21.81	21.81
2	2.65	13.94	35.75
3	2.06	10.83	46.57
4	2.01	10.57	57.15
5	1.68	8.84	65.99
6	1.08	5.67	71.66

Table 5-8: Total variance explained by the CPT components

Components	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	3.09	23.76	23.76
2	1.73	13.30	37.05
3	1.51	11.62	48.67
4	1.36	10.49	59.16

Table 5-9: Total variance explained by the components for the integrated theories

Components	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	4.91	18.18	18.18
2	4.05	14.99	33.17
3	2.45	9.06	42.23
4	2.01	7.45	49.68
5	1.76	6.50	56.18
6	1.40	5.19	61.37
7	1.32	4.87	66.24
8	1.28	4.73	70.97

In order to identify the effect size of the original variables on each component, Tables 5-10, 5-11 and 5-12 show the correlation between the component and each variable. In other words, this rotated component matrix explains the contribution of each variable in this component. By taking into account the variables that have strong loadings in the components, each component retained in the model can be interpreted as follows.

- **RAT components**

Percentages of male employed, non-Saudis, households with no vehicles (HNV), had very strong positive loadings on the first component, whereas percentage of students and the average family size had strongly negative factor loadings. This component can reflect foreign workers, as non-Saudis typically have a lack of access to vehicles and the majority of them are workers. The second component, the density of male population and roads classified as E, B and C, had highly positive correlations with this factor. This PCA can be described as “high density of male population and roads” (see Table 5-10).

The third component loads strongly and positively on percentage of females employed, diversity index, density of collector roads classified as D, whereas it loaded negatively but less strongly on percentage of housewives. This component can be labelled as “female employed with high diversity”. The fourth one, percentage of people who were single and male population aged between 15 and 24, was strongly positively correlated with this component, whereas percentage of housewives was strongly negatively correlated. This component can be interpreted as “single and young people”. For the fifth component, percentage of people who were unemployed, the percentage of households who were renters and percentage of people with low or no educational qualifications (LNEQ), were positively loading on the component. This fifth component is a reasonable representation of the poverty level (see Table 5-10).

The final component, as indicated earlier, is that freeways “A” had very weak correlations with independent variables so it had its own component with the highest positive correlation with the sixth component. Fabrigar et al. (1999) and Leech et al. (2014) suggested that an appropriate factor should have at least four variables. Leech et al. (2014) proposed that the weaker components be excluded from the analysis, or that the PCA should be rerun after removing the variable with very weak correlations. However, for the purpose of examining RAT in order to determine the significance of various types of roads, the component representing freeways was included in the present analysis (see Table 5-10).

Table 5-10: Rotated component matrix for the RAT components

Variables	Components					
	1	2	3	4	5	6
Students	-0.914	====	====	====	====	====
Employed males	0.914	====	====	====	====	====
Non-SA males	0.857	====	====	====	====	====
HNV	0.695	====	====	====	====	====
Average of family size	-0.642	====	====	====	0.366	====
Roads E	====	0.867	====	====	====	====
Male population density	====	0.825	====	====	====	====
Roads B	====	0.691	====	====	-0.305	====
Roads C	====	0.667	====	====	====	====
Employed females	====	====	0.771	====	====	====
Diversity	====	====	0.696	====	====	====
Roads D	====	====	0.538	====	====	====
Single	====	====	====	0.834	====	====
Housewives	====	====	-0.405	-0.709	====	====
Age 15-24	-0.522	====	====	0.623	====	====
Unemployment	====	====	====	====	0.732	====
Renters	====	====	0.346	====	0.639	====
LNEQ	0.473	====	-0.377	0.429	0.482	====
Roads A	====	====	====	====	====	0.954

- **CPT components**

  From Table 5-11, the density of facilities, local roads classified as E and percentage of apartment buildings had very strong positive loadings on the first component. This component reflects areas with a high density of facilities. For the second component, the density of collector roads classified as D and residential areas had highly positive correlations with this factor. This PCA can be described as having a ‘High density of residential land use’.

The third component was loaded strongly and positively with the density of car facilities and car parks. Hence, this component can be labelled ‘Car facilities”. The percentage of recreational land use was strongly and positively correlated with the fourth component. This component can be labelled ‘Recreational and entertainment land use’.

Table 5-11: Rotated component matrix for the CPT components

Variables	**Component**			
	1	**2**	**3**	**4**
Facilities	0.844	====	====	====
Roads E	0.829	====	====	====
Apartment buildings	0.809	====	====	====
Roads B	0.676	====	====	====
Roads C	0.609	====	====	====
Roads D	====	0.694	====	====
Industrial land use	====	-0.649	====	====
Residential areas	-0.346	0.559	-0.368	-0.307
Car facilities	====	====	0.75	====
Car park	====	-0.484	0.602	====
Roads A	====	====	-0.599	0.3
Recreational and entertainment	====	====	====	0.827
Commercial areas	====	====	====	0.47

- **Integrated theories components**

The percentages of employed males, non-Saudis and HNV had very strong positive loadings on the first component, whereas the percentage of students and average family size had strongly negative factor loadings. This component can be labelled ‘Foreign workers’. The density of males, roads classified as E, B and C and the facilities had highly positive correlations with the second component. This PCA can be described as ‘High population density and density of facilities’ (see Table 5-12).

The percentage of employed females, the diversity index, the density of roads classified as D and residential areas had strong positive loadings for the third component. This component can be labelled ‘Employed females and high diversity residential areas’. The percentage of single people, the male population aged between 15 and 24 and the percentage of people with low or no education qualifications had strong positive correlations with the fourth component. This component can be labelled ‘Single and young people’. The percentage of unemployed people, the percentage of renters and the percentage of people with low or no educational qualifications had positive loadings on the fifth component. This fifth component can reflect the poverty level.

The percentage of housewives and the percentage of commercial areas had positive correlations with the sixth component, whereas the percentage of industrial land use had a strong negative correlation with the sixth component. This component can be called ‘Housewives and commercial areas’. The percentage of recreational and entertainment land use had strong loadings on the seventh component, whereas the freeways classified as ‘A’ had strong positive loading on the eighth component (see Table 5-12).

Table 5-12: Rotated component matrix for the integrated theories components.

Variables	Component							
	1	2	3	4	5	6	7	8
Students	-0.907	===	===	===	===	===	===	===
Employed males	0.884	===	===	===	===	===	===	===
Non-SA males	0.799	0.376	===	===	===	===	===	===
HNV	0.684	===	===	===	===	===	===	===
Average of family size	-0.638	===	===	===	0.36	===	===	===
Age 15-24	-0.624	===	===	0.51	===	===	===	===
Car Facilities	0.426	===	===	0.384	===	===	===	-0.406
Male population density		0.857	===	===	===	===	===	===
Roads E		0.839	===	===	===	===	===	===
Facilities	0.304	0.749	===	===	===	===	===	===

Apartment buildings	0.449	0.691	===	===	===	===	===	===
Roads B		0.677	===	===	-0.336	===	===	===
Roads C	===	0.604	===	===	===	===	===	===
Employed females	===	===	0.748	===	===	===	===	===
Diversity	===	===	0.659	===	===	===	===	===
Roads D	===	===	0.633	===	===	===	===	===
Residential areas	-0.384	===	0.526	===	===	===	===	===
Single	-0.326	===	===	0.833	===	===	===	===
LNEQ	0.363	===	-0.342	0.519	0.43	===	===	===
Car Parks	0.352	===	===	0.465	===	===	===	-0.315
Unemployment	===	===	===	===	0.71	===	===	===
Renters	===	===	===	===	0.568	===	===	===
Industrial Land Use	0.353	===	===	===	===	-0.701	===	===
Housewives	===	===	-0.388	-0.474		0.565	===	===
Commercial areas	===	===			-0.398	0.495	===	===
Recreational and entertainment	===	===	===	===	===	===	0.914	===
Roads A	===	===	===	===	===	===	===	0.843

As the integration of variables representing both RAT and CPT provide a full picture for the characteristics of the study area of Riyadh, it is helpful to provide a description of the spatial distribution of the PCA scores across the study area. Understanding the distribution of these features will contribute to identifying the effects of each component on MVT rates when we are referred back to these maps in the discussion in Chapter 8.

Spatial distributions of the PCA scores that represent the integration of the theories:

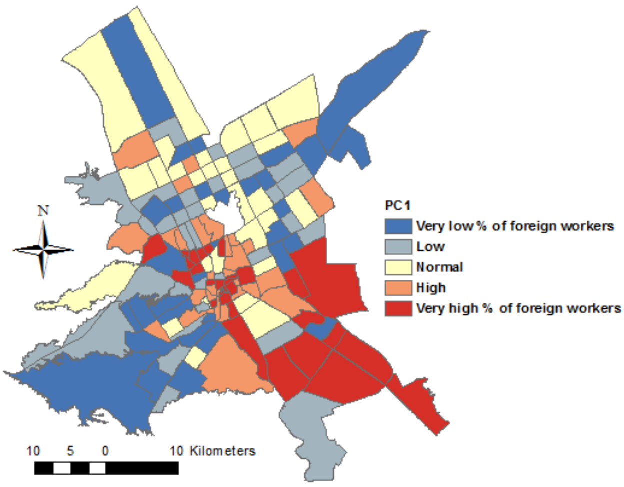
PC1: Foreign workers' – (Figure 5-3A)– concentrates heavily on the central districts and south-east of the city.

PC2: High density of male population and facilities – (Figure 5-3B) – show a high concentration in the central areas and some parts of the eastern areas.

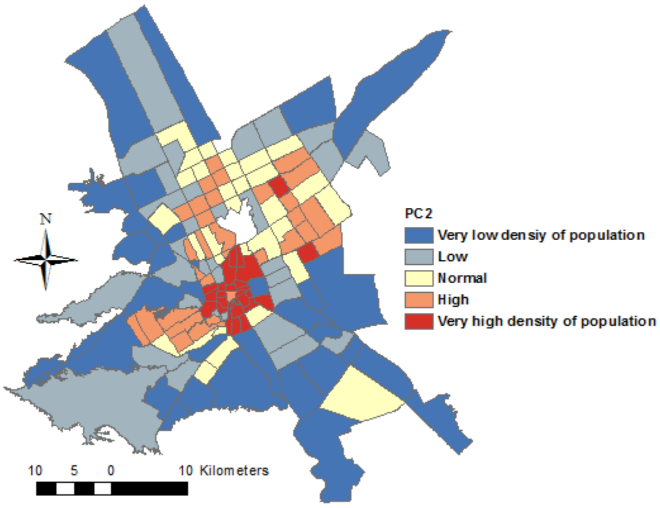
PC3: Employed females and high diversity residential areas– (Figure 5-3C)– present a high concentration in the north of the city.

PC4: Single and young people – (Figure 5-3D) tend to cluster heavily in the west, north-west and south of the city.

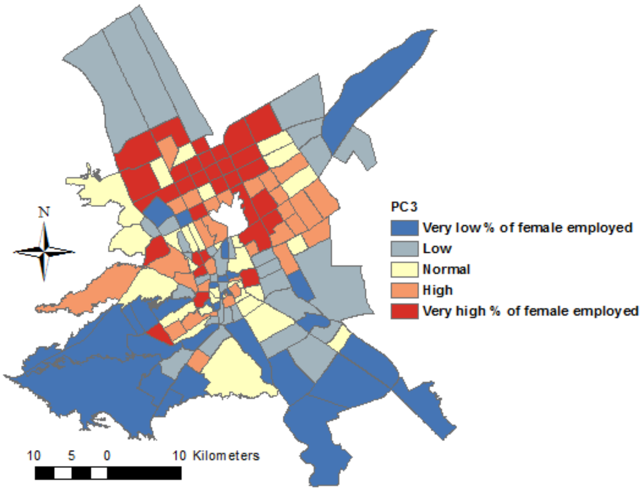
PC5: Low social and economic conditions "poverty" – (Figure 5-3E); there is a high concentration of these conditions in some parts of the central districts, south-western areas and eastern neighbourhoods.



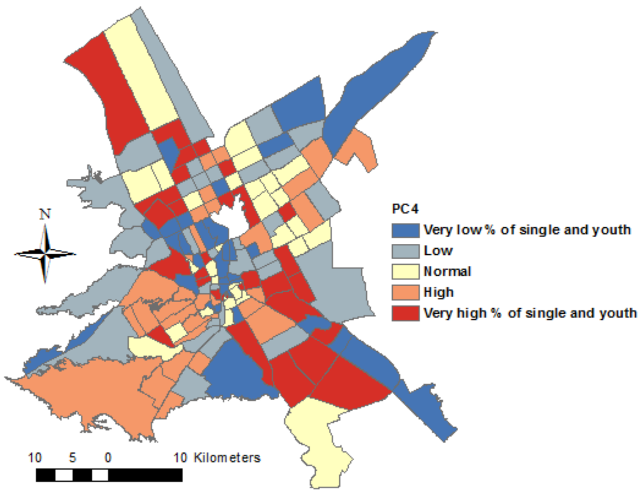
A. Spatial distributions of PC1 scores across the study area, Riyadh



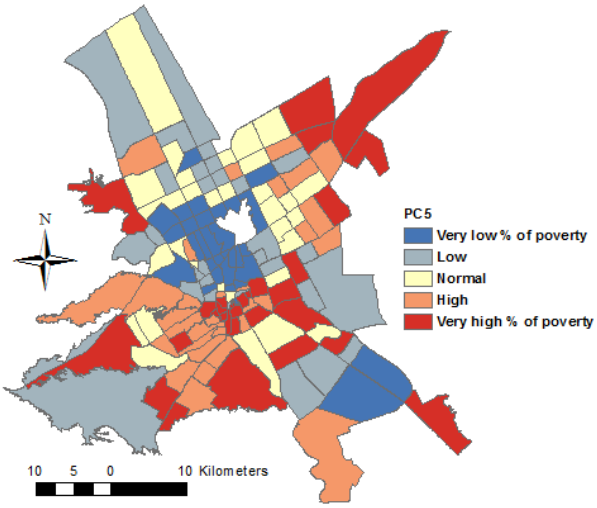
B. Spatial distributions of PC2 scores across the study area, Riyadh



C. Spatial distributions of PC3 scores across the study area, Riyadh



D. Spatial distributions of PC4 scores across the study area, Riyadh



E. Spatial distributions of PC5 scores across the study area, Riyadh

Figure 5-3: Spatial distribution of the PCA scores across the study area, Riyadh

5.4.2.3 Testing Spatial Autocorrelation

In this study, the reason for detecting spatial autocorrelation at a global level is to test the assumption of spatial independence amongst the residuals yielded from applying OLS and GWR regression models (Charlton and Fotheringham, 2009).

Values of points can be spatially correlated to each other in the form of one of the three degrees: positive autocorrelation, negative autocorrelation or no autocorrelation (zero autocorrelation) (O'Sullivan and Unwin, 2010). Positive spatial autocorrelation, means that nearby values of points tend to be more similar (clustered) than those distant values of points while negative autocorrelation occurs when dissimilar values of points (geographical locations) tend to be closer together (similar data dispersed) (Bernasco and Elffers, 2010; Getis, 2010; O'Sullivan and Unwin, 2010). In contrast, zero spatial autocorrelation reveals that values of points are independent from each other, indicating that the spatial distribution of these points varies randomly over space (random pattern) (O'Sullivan and Unwin, 2010). Spatial autocorrelation can be measured locally and globally. In this study, global index Moran's I (Moran, 1950) was used to measure the degree of spatial autocorrelation globally. The global Moran's I is usually used to test the spatial autocorrelation for the residuals from regression models (Charlton and Fotheringham, 2009; Wallace et al., 2006). It can be used for both points and polygons. Moran's I is a linear measure and analogous to Pearson's correlation coefficient (Getis, 2010; Anselin et al., 2000). In order to measure the spatial autocorrelation, Moran's I works according to the following formula (Sawada, 2001):

$$I = \frac{n}{\sum_{i=1}^{i=n}\sum_{j=1}^{j=n} w_{ij}} \frac{\sum_{i=1}^{i=n}\sum_{j=1}^{j=n} w_{ij}\,(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{i=n}(x_i - \bar{x})^2}$$

Where W_{ij} is the connectivity weight matrix of the cross-product statistic to describe the relation between geographical units *i* and *j*.

n indicates the number of observations (points or polygons).

$\bar{x}$ indicates the average of the observations

x_i indicates the value of the observations (at location)

x_j indicates the value of the observations (another location).

In order to conduct the global Moran's I, a spatial weight matrix is required. The matrix indicates the relationship between geographical units and their neighbours (Aldstadt, 2010; Anselin et al., 2000; Getis, 2010; O'Sullivan and Unwin, 2010). Generally, a spatial weights matrix (w) is a square matrix formed of elements w_{ij} that represent the observations *ij* in spatial data, in which each column and row in the matrix corresponds to each observation pair *ij* (Aldstadt, 2010; Anselin et al., 2000; Getis, 2010; O'Sullivan and Unwin, 2010). It is important to indicate that using different techniques for spatial weight matrix can produce different values for relationships between observations and their neighbours, leading to different results (Benjanuvatra, 2013). In this study, the inverse distance technique was used as a spatial weight matrix. The inverse distance method has been adapted to identify the spatial relationship between observations in order to conduct a global Moran's I test for detecting spatial autocorrelation amongst residuals yielded from regression models (Charlton and Fotheringham, 2009; Almeida et al., 2005). The idea of the inverse distance method is that neighbouring locations have greater impacts than locations at a farther distance (Mateu and Müller, 2012). The global Moran's I was conducted through ArcGIS software. The results for detecting spatial autocorrelation will be described later in Chapter 7, which presents the results from the regression models.

5.4.2.4 Multinomial Logistic (ML) Regression Model

In this analysis, the ML model was used to study the effect of the predictors on the probability of MVT occurrences in the four time periods under the RAT, the CPT and the integrated theory. It was used to investigate how the explanatory variables influenced MVT occurrence during the day. The use of the ML has advantages. First, in this regression model, the dependent variable is MVT incidents, which were measured at the nominal level with four categories of responses: Period One, Period Two, Period Three and Period Four, whereas in the OLS regression, the MVT rates are presented as continuous data. Thus, the dependent variables in this ML regression represented the time periods during which each MVT incident was coded to represent a time of these periods. This allowed a comparison between the time periods and identify how the independent variables vary in their effects on the probability of MVT occurrences throughout the day. In addition, it is indicated in Chapter 2 that ML regression has fewer restrictions than the OLS regression (Starkweather and Moske, 2011). Thus, identifying the relationships between MVT and explanatory variables from different types of regression models can be complementary.

In order to run the ML model, the dependent variable must be measured at the nominal level. Therefore, the MVT data were divided into four time-period categories: 12 am to 6 am, which was coded as ‘1’; 6 am to 12 pm, which was coded as ‘2’; 12 pm to 6 pm, which was coded as ‘3’; and 6 pm to 12 am, which was coded as ‘4’. Furthermore, all the independent variables were measured as continuous. The strategy for fitting the ML models was to use the stepwise techniques.

In multinomial regression, one of the response variable’s categories is considered a reference category. In this study, we used Period One as the reference, although different outputs would not be expected if we used a different time period as the reference; the results would be the same.

The general formula for the ML model is as follows (Britt and Weisburd, 2010):

$$P(Y = m) = \frac{\exp(Xb_m)}{\sum_{j=1}^{J} \exp(Xb_j)}$$

In this equation, $P(Y = m)$ represents the probability for the dependent variable (Y), m refers to the outcome category and has values ranging from 1 to J (the last category); the numerator exponentiates the value of Xb for category m; and the denominator exponentiates the value of Xb for all categories, and then it sums these values.

Diagnosing the Regression Model

ML regression requires fewer assumptions and restrictions than OLS regression (Starkweather and Moske, 2011). It assumes no multicollinearity between the independent variables. This assumption was met, since the regression used the components that were uncorrelated (Jackson, 2005). Furthermore, ML regression assumes no outliers and high leverage values. ML regression in SPSS does not provide any diagnostic statistics detecting outliers. Therefore, the outliers were detected by conducting binary logistic regression for the four categories by comparing Period Two to Period One, Period Three to Period One and Period Four to Period One. For the purpose of detecting extreme outliers, we identified whether studentised residuals greater than ± 2 existed (Chen et al., 2013). Tables 5-13, 5-14 and 5-15 show the studentised residuals, and we can see that no extreme values that violated the assumptions existed, since the residuals did not exceed ± 2 (the minimum value was -2.06 ≅ -2 and the maximum value was 1.19). The results of the models are presented in Chapter 7.

Table 5-13: Studentised residuals for RAT model

Studentised residual	Minimum	Maximum
Periods One and Two	-1.90813	-1.18513
Periods One and Three	-1.68594	-1.15118
Periods One and Four	-1.89207	1.19567

Table 5-14: Studentised residuals for CPT model

Studentised residual	Minimum	Maximum
Periods One and Two	-1.92783	-1.12064
Periods One and Three	-1.85121	-1.20216
Periods One and Four	-1.82778	1.02412

Table 5-15: Studentised residuals for the integrated model

Studentised residual	Minimum	Maximum
Periods One and Two	-2.06345	-1.20958
Periods One and Three	-1.99557	-1.13869
Periods One and Four	-1.89865	1.21084

5.4.2.5 Geographically Weighted Regression (GWR)

In this study, GWR was used to overcome the issue of the existing spatial autocorrelation between the residuals yielded from some OLS regression models, which violates the regression assumptions (see Chapter 7). In addition, it was used to account for spatial heterogeneity as suggested by a number of studies (Bruna and Yu, 2013; Leung et al., 2000; Brunsdon et al., 1996). Therefore, GWR in this study was used only with the integrated model as the final regression model to improve prediction of MVT rates at the local level, which is based on the PCA components. The use of GWR can improve the regression models in terms of capturing the spatial variations in relation to the influence of predictor variables for the MVT rates, since the influence of the predictors is not constant over the study area (Brunsdon et al., 1996). The GWR provides a spatially varying set of parameters to evaluate the relationship between a dependent variable and an independent variable, which can be used to produce maps for the study area for visualisation.

The general formula for this regression (Wheeler and Tiefelsdorf, 2005) is as following:

$$y_i = \beta_{i0} + \sum_{k=1}^{p} \beta_{ik} x_{ik} + \varepsilon_i , \qquad i = 1, \dots, n,$$

Where:

- y_i represents dependent variable for location i.
- x_{ik} represents the value of the k independent variable at location i.
- β_{i0} represents the intercept of the true regression line at location i .
- β_{ik} represents the local regression coefficient “the slope” for the k the independent variable at location i.
- ε_i represents the random error at location i.
- p represents the number of independent variables in the model.

It is suggested firstly to conduct OLS regression in order to fit the regression model through identifying the key variables, and then GWR can be used (Charlton and Fotheringham, 2009). Thus, in this study, GWR was implemented using the same predicted PCA scores that were produced by the OLS model for MVT rates under the integration of RAT and CPT. The adaptive kernel was adopted for the GWR because this method was relevant for the spatial data, which varied across the study area due to heterogeneous polygons (Lin and Wen, 2011). In order to test the assumption that there should be no spatial autocorrelation correlation, the global Moran's I was used as explained in Section 5.4.2.3. The results of the GWR model for the integrated theories are interpreted in Chapter 7.

To sum up, Section 5.4 describes in detail the process for implementing several spatial and statistical methods in order to understand the MVT that occurred in Riyadh from 2012 to 2014 during the four periods of the day. The first part of the analysis methods focused on describing the spatial distribution of the MVT spatial patterns throughout the day utilising a mapping technique and the spatial point pattern test illustrated in Section 5.4.1. The second part (Section 5.4.2) aimed to explain why the spatial patterns of MVT occurred in certain neighbourhoods and at particular periods of time.

5.5 Chapter Summary

This chapter has presented the datasets and methods employed in this thesis. The chapter showed that recent data was obtained for Riyadh's MVT problem and the characteristics of the city neighbourhoods. The data were prepared for analysis on the basis of the theoretical framework developed for this study. The MVT was divided into four periods of the day representing the patterns of Saudi daily routines according to RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993). The socioeconomic, demographic and built environment characteristics of Riyadh's neighbourhoods were described in Section 5.3.3, which outlines how each variable related to relevant elements of RAT and CPT. For example, the young male population aged 16-24 were used to represent motivated offenders – (RAT), whereas the density of facilities were used to represent MVT attractors – (CPT).

Section 5.4 explained the spatial and statistical methods adapted for the analysis of the data on the basis of examining two major ideas of RAT and CPT. To do so, the goal of the first part of the analysis methods is to examine the first idea of the theories, which suggests that crime varies in its occurrence over space and throughout the day (Section 5.4.1). This was achieved in two steps. First, the mapping technique was conducted to provide some understanding of the spatial distribution of MVT across the study area during the four periods. Second, the use of spatial point pattern tests to detect significant differences between the spatial patterns of MVT occurrence across the study area and during the four periods was illustrated in Section 5.4.1.2. The results of the first part of the analysis will be presented in Chapter 6.

The second part of the analysis is based on the second core idea of RAT and CPT, which aimed to identify and predict the factors that contributed to MVT concentrations in certain neighbourhoods and during certain time periods of the day. Completing this task provides understanding for the MVT problem through use of the Western environmental criminology approach. Section 5.4.2 described the regression analysis techniques which were implemented to accomplish this goal. Determining the statistically significant relationships between MVT and the different variables was achieved at two levels: the global level and the local level. At the global level, the OLS and ML regression models were used. A number of crucial assumptions were taken into account in order to run OLS regression models such as normality for the dependent variable (Leech et al., 2005) and little or no multicollinearity between the independent variables (Pringle, 1981). In order to combat the issue of multicollinearity and reduce the number of variables, the PCA was used as described in Section 5.4.2.2.

The chapter presented how the ML regression was adopted in this study as a different type of regression from the OLS regression. It was used to determine the significance of explanatory factors in terms of their influence on the probability of MVT occurring in the four time periods (in Section 5.4.2.4). Since this study is based on spatial data, so the spatial autocorrelation and spatial heterogeneity are important aspects of the spatial analysis of MVT patterns. With regard to the spatial autocorrelation, the residuals yielded from OLS and GWR regression models were detected using the global Moran's I, as illustrated in Section 5.4.2.3. Finally, the chapter has shown the use of GWR to examine the relationships between the MVT and several factors representing the integrated theories at the local level – spatial heterogeneity, and also to overcome any existing spatial autocorrelation amongst residuals yielded from the OLS regression models. The results from modelling MVT will be shown in Chapter 7.

Having described the data and methodologies applied in this study, the next chapter will present and describe the results yielded from the exploratory analysis of MVT data.

Chapter 6

Exploratory Analysis of Spatial-Temporal MVT Patterns

6.1 Introduction

The previous chapter has described the obtained data and explained the techniques used for employing this data in achieving the thesis objectives. This is a short chapter that will present the results yielded from implementing the simple spatial-temporal techniques; mapping and the use of the spatial point pattern test to investigate whether the spatial patterns of MVT occurrences significantly change from morning to afternoon, from afternoon to evening, and so on, as a result of changes in people's routine activities. This will test the first principal theme of both theories, namely that crime incidents tend to have a high frequency of occurrence at particular times and in particular places, and that these are strongly influenced by the routine activities of those involved. This is a fundamental step for achieving the major aim of this thesis, as identifying the concentration of MVT in certain neighbourhoods during certain periods of time leads to subsequent analysis for investigating factors that contributed to these concentrations and variations in spatial patterns of MVT in Chapter 7.

The chapter is divided into three sections, as follows. The first Section 6.2 visualises and describes the spatial distribution of MVT rates throughout the day. The second Section 6.3 aims to identify the significant changes or differences in the MVT incidents that occurred during the four different time periods. The final Section 6.4 provides a summary of this chapter.

6.2 Spatial Distribution of MVT Rates in Riyadh

This section explores the spatial distribution of MVT rates obtained from the CPS database in order to identify the daily rates for Period One (12 am to 6 am), Period Two (6 am to 12 pm) and Period Three (12 pm to 6 pm) and Period Four (6 pm to 12 am). As explained in Chapter 5, these periods were selected on the basis of the RAT and CPT as crime opportunities vary throughout the day. Thus, the day was divided according to the practised daily routines in SA. No previous studies have examined MVT based on the RAT and CPT during different time periods throughout the day.

Since the spatial analysis of MVT patterns in Riyadh was carried out at a neighbourhood level, it is more likely that areas with a high density of vehicles tend to have more MVT incidents, which can produce misleading analysis results. This issue was controlled by taking into account the object at risk—the vehicle—by calculating MVT rates as discussed in Chapter 5.

The below maps in Figures 6-1 and 6-2 are classified using the quantile method described in Chapter 5 since this classification is useful for comparing between maps (GeoSWG, 2012; Boba, 2005). Using quantiles with five classes, the top 20% of neighbourhoods with the highest MVT rates can be identified, as well as the bottom 20% of the neighbourhoods with the lowest MVT rates. From Figure 6-1, which shows the MVT rates for the entire day, it can be seen that the highest MVT rates tended to cluster in the central districts, southern areas and some neighbourhoods in the eastern areas. In contrast, the northern and western areas showed lower MVT rates.

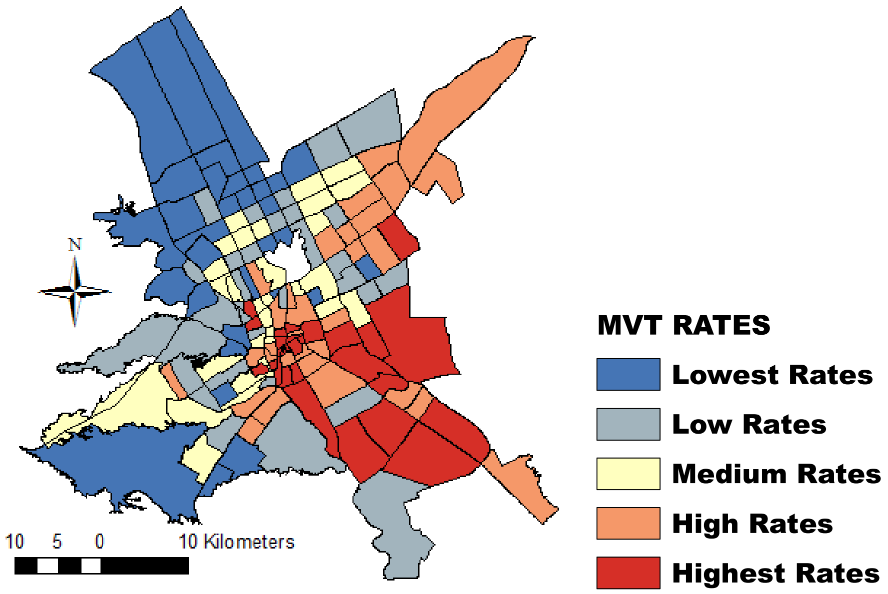
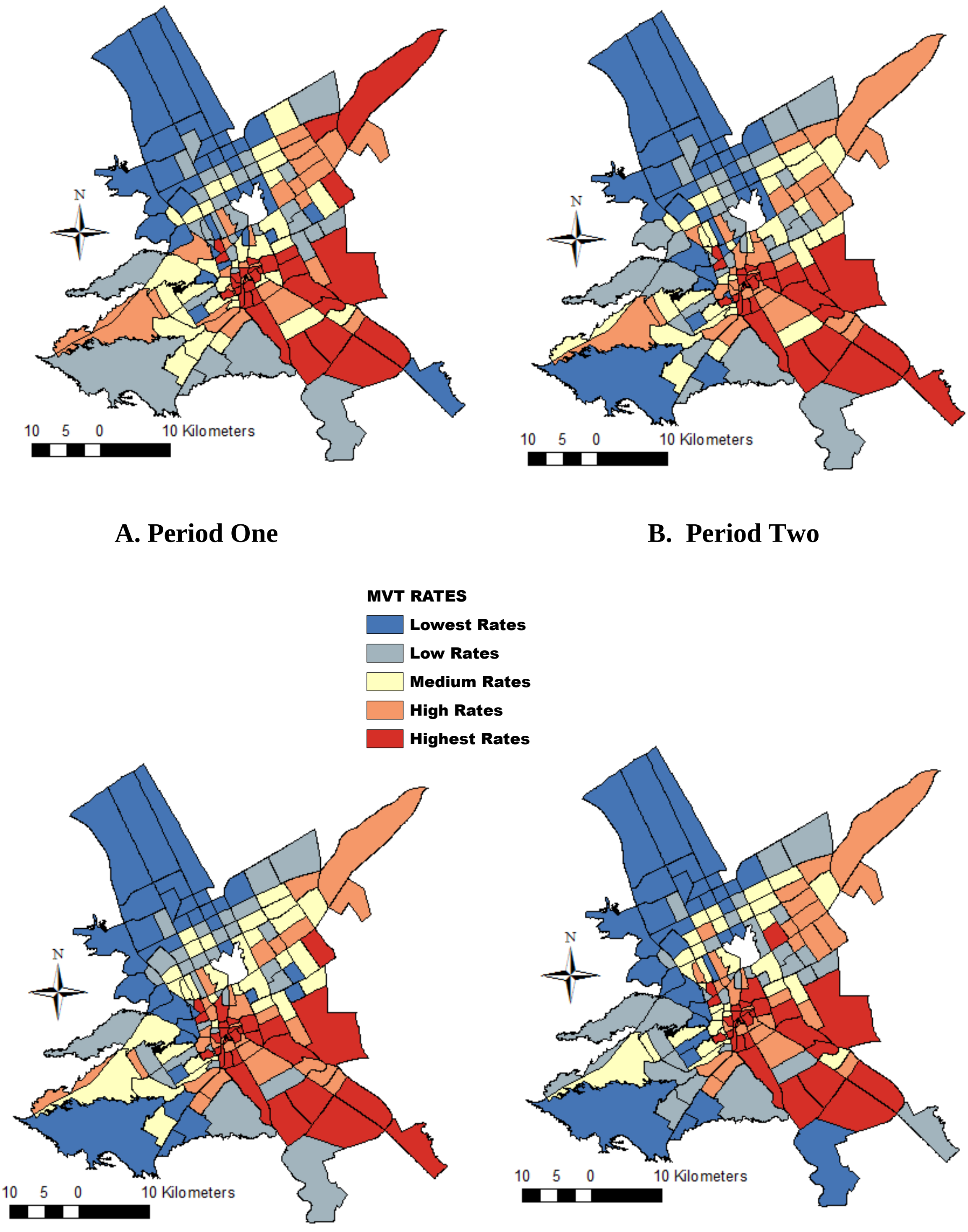


Figure 6-1: Spatial distribution for overall MVT rates in Riyadh, 2012 to 2014

Figure 6-2 shows the spatial distribution across Riyadh of the average rates in the four periods of the day for the same period from 2012 to 2014. It is clear that the high MVT rates during all time periods were heavily concentrated in several districts, particularly in the centre of Riyadh and in several districts in the southern neighbourhoods. The city centre and other inner-city areas showed a high concentration of high rates. Moreover, MVT rates during Period Four showed high rates in southern and eastern districts in Riyadh (Figure 6-2D). The few of neighbourhoods exhibited some high MVT rates in the western areas during Periods One, Two and Three, whereas no hot spots were shown in Period Four in these areas. On the other hand, there were lower rates of motor vehicle thefts in the northern neighbourhoods located in the outskirts of the city.



A. Period One **B. Period Two**

C. Period Three **D. Period Four**

Figure 6-2: Maps illustrating MVT rates throughout the four study periods in Riyadh from 2012 to 2014.

Since we have visualised and identified the spatial distribution of MVT rates within Riyadh's neighbourhoods, this allows us to grasp some understanding of the spatial distribution of MVT patterns, specifically the description of the occurrence. However, it is critical to determine whether spatial patterns of MVT significantly change from period to period throughout the day, focusing on the basic idea of RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) that crime opportunities vary over space and time. The following section will achieve the previous goal.

6.3 Are these Spatial Patterns of MVTs Statistically Different?

The purpose of this section is to identify whether there are significant changes or differences between the MVT incidents that occurred during the four time periods. In order to achieve this goal and remembering that we have point data for CPS, the Andresen's spatial point pattern test (Andresen, 2009) (as discussed in Section 5.4.1.2) was performed. As mentioned in Chapter 2, the spatial point pattern test has been used in different areas of the criminology field (Andresen et al., 2016; Hodgkinson et al., 2016; de Melo et al., 2015; Andresen and Malleson, 2013; Andresen and Linning, 2012; Andresen and Malleson, 2010).

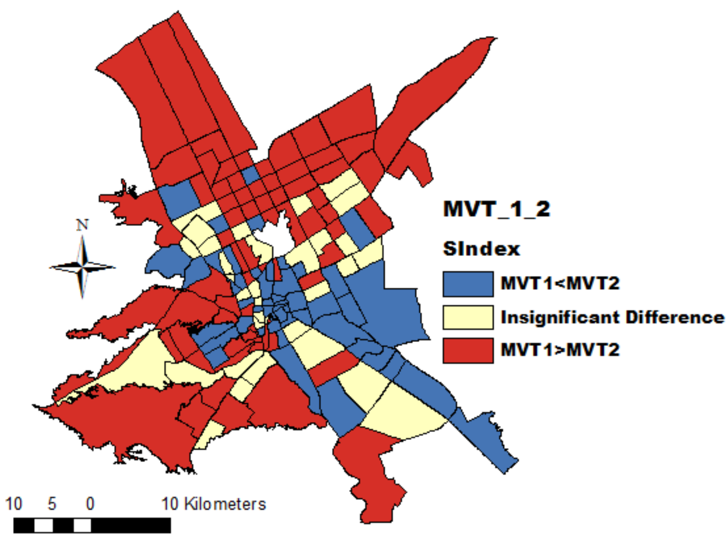
Recall that the S index will be 1 for two point patterns that are identical and 0 for two that are dissimilar. By looking at Table 6-1 below, it is clear that the results show that there were statistically significant differences in the occurrence of MVT incidents across the study region during the four time periods, as the global S index values ranged from 0.21 to 0.33.

Table 6-1: Spatial point pattern test output, S-Indices, MVTs in Riyadh

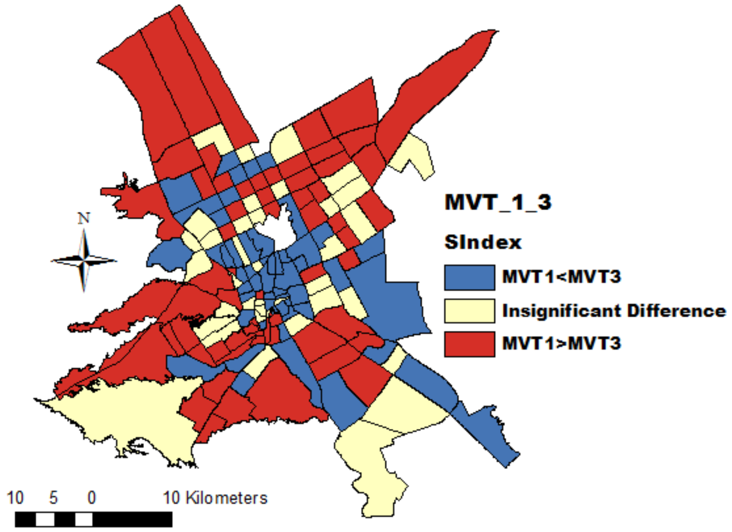
MVTs	Period One	Period Two	Period Three	Period Four
	12 am – 6 am	6 am -12 pm	12 pm- 6 pm	6 pm -12 am
Period One	1	===	===	===
Period Two	0.210	1	===	===
Period Three	0.242	0.337	1	===
Period Four	0.210	0.273	0.267	1

The local S index can also be used to identify statistically significant changes in crime patterns in local areas. Values are either +1 when the base dataset has a significantly higher proportion of events than the test dataset and -1 when it is vice versa, indicating a significant difference, or a value of 0, meaning insignificant difference (Andresen, 2009). As explained in the methodology Section 5.4 in Chapter 5, the base dataset and test dataset were chosen based on chronological order. Therefore, the analysis started by comparing Period One (12 am to 6 am) as the base dataset and Period Two (6 am to 12 pm) as the test dataset, then Period Two as the base dataset to Period Three as the test dataset and so on. Thus, all periods were compared to each other in order to detect significant statistical differences between spatial patterns of MVT throughout the day.

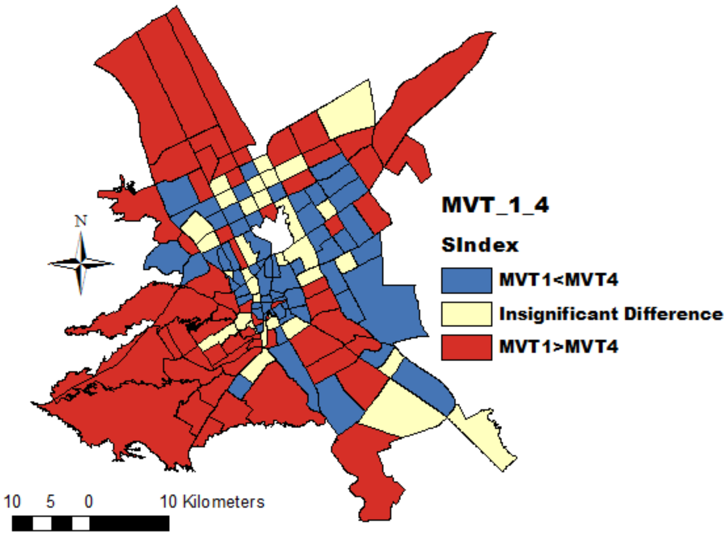
The maps in Figure 6-3 indicate that the spatial patterns of MVTs during Period One tended to exhibit significant differences across the study area from those in Period Two (Figure 6-3A), Period Three (Figure 6-3B) and Period Four (Figure 6-3C). A few neighbourhoods showed no significant difference in spatial patterns. The interesting finding here is that MVT tended to present higher concentrations during Period One in the outskirt areas in comparison to the later time periods. This could indicate that these areas might have some characteristics that contributed to them being targeted more during the sleeping hours (Period One) than during the other time periods.



A. Period One (base dataset) and Period Two (test dataset)



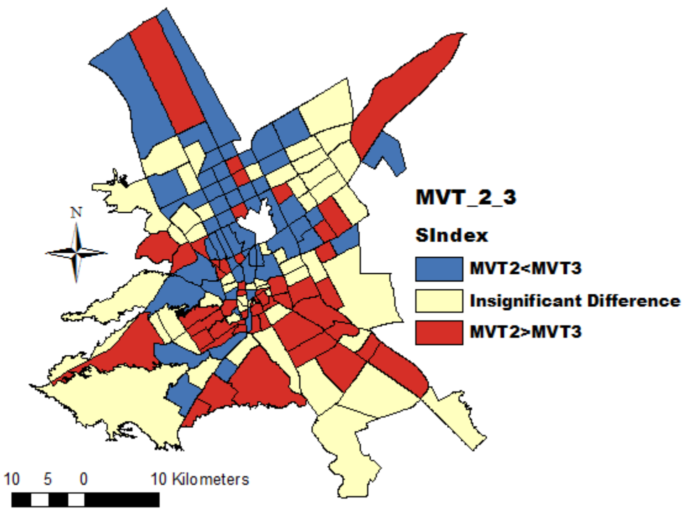
B. Period One (base dataset) and Period Three (test dataset)



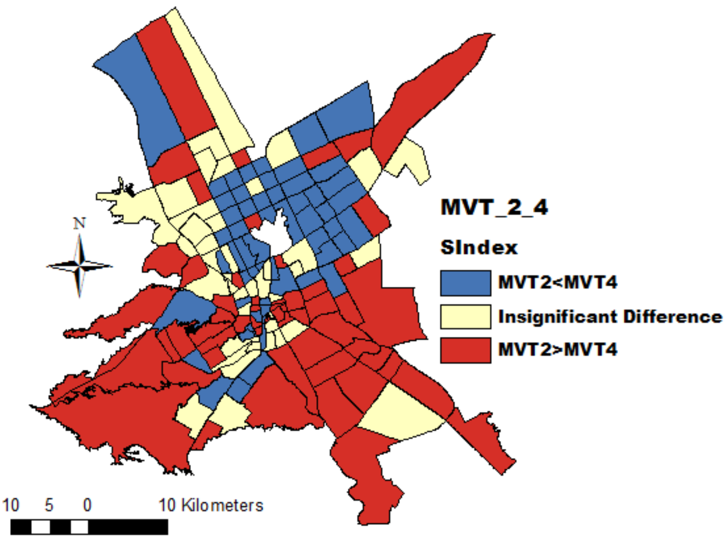
C. Period One (base dataset) and Period Four (test dataset)

Figure 6-3: Significant differences in MVT incidents between Period One and the other time periods

The maps below (Figure 6-4) compare Period Two with Periods Three (Figure 6-4A) and Period Four (Figure 6-4B). The maps show more significant differences in MVT occurrences between Periods Two and Four (Figure 6-4B) than between Periods Two and Three (Figure 6-4A). Furthermore, MVTs during Period Two versus the rest of the day, shows that Period Two had increased concentrations of MVTs in the southern areas in comparison to the other periods. On the other hand, Period Two showed significantly fewer concentrations of MVT in neighbourhoods located in the northern and eastern areas than Periods One, Three and Four.



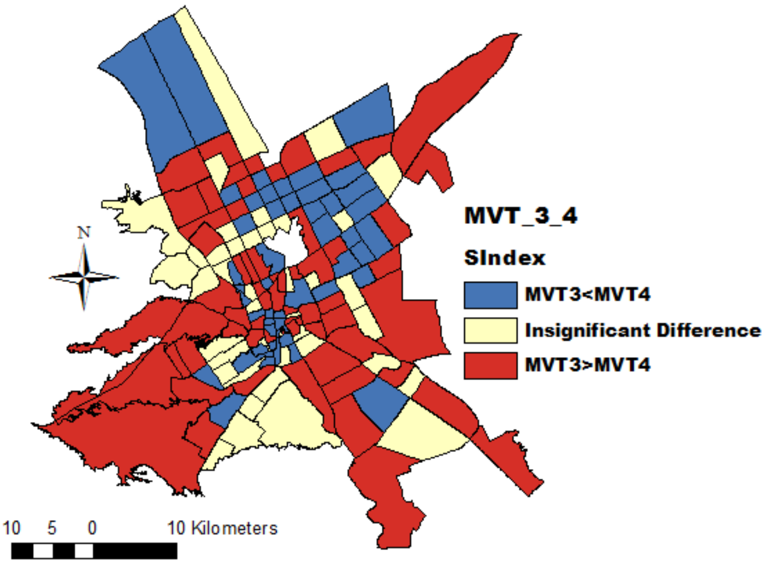
A. Period Two (base dataset) and Period Three (test dataset)



B. Period Two (base dataset) and Period Four (test dataset)

Figure 6-4: Significant differences between MVT incidents between Period Two and Periods Three and Four.

Figures 6-3C, 6-4B and 6-5 show the differences in MVT between Period Four and Periods One, Two and Three, and this suggests the following important results. First, the maps show significant differences in MVT occurrences between Period Four (evening) and the rest of the day (morning, afternoon and sleeping hours). Furthermore, it is notable that the majority of the northern and eastern areas exhibited significantly higher concentrations of MVT incidents during Period Four than during the other time periods. In contrast, the western and southern areas had a significantly lower proportion of MVT incidents in Period Four than in Periods One, Two and Three.



Period Three (base dataset) and Period Four (test dataset)

Figure 6-5: Significant differences between MVT incidents that occurred during Period Three and Four

Overall, the analysis based on the spatial point pattern test enabled us to identify significant differences in MVT between the different time periods. For example, the results indicate that MVT incidents tended to show higher concentrations during Period One in the outskirt areas, during Period Two in the southern neighbourhoods and during Period Four in northern and eastern areas. Another interesting result was that the spatial patterns of MVTs during Period Four showed the greatest differences from those in Periods One, Two and Three. The differences in the spatial patterns throughout the day might have been caused by various factors that contributed to the MVT incidents during these periods. For instance, the periods differ in their routine activities, as Period One is typically sleeping hours, Period Two is typically working hours, Period Three is the rest after working hours and Period Four is typically leisure and shopping hours. The overall results strongly support the ideas of RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993), which state that crime opportunities are likely to vary in their frequency among certain locations at particular times of day due to daily activities.

6.4 Summary of Chapter 6

This short chapter has explored MVTs throughout the day. The analysis began by visualising the spatial distribution of MVT rates throughout the day. Then, the MVT data were investigated to reveal whether there were significant differences between the MVT occurrences at different times. The overall results of this chapter emphasise that the high MVT rates were spatially concentrated in the central districts, southern and eastern neighbourhoods throughout the day. However, the spatial point pattern test suggested that there were significant differences between MVT occurrences throughout the day. As every period of day tended to have more MVT incidents compared to other periods in particular places, for instance Period One in the outskirt areas, during Period Two in the southern neighbourhoods and during Period Four in northern and eastern areas. These significant differences lead us to expect that the factors that contributed to these differences in location and time were different, or at least varied in terms of their influence on MVT occurrences, throughout the day. Therefore, the following chapter will examine selected factors using the theoretical framework designed under RAT and CPT.

Chapter 7

Modelling MVT

7.1 Introduction

Chapter 6 focused on performing spatial and temporal analysis on the MVT data. It found that there were significant differences between the MVT occurrences from one period to another (Section 6.3). This suggests that significant differences could be caused by the surrounding socioeconomic, demographic and environmental factors. Both RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) suggest that spatial patterns of crime tend to show variations across locations and among time periods as a result of variations in routine activities for people from different backgrounds. Thus, it is expected that spatial and temporal patterns (presented in Chapter 6) were influenced by specific factors that contributed to MVT occurrences during certain periods. Furthermore, each factor varies in its influence on MVTs from one period to another as a result of shifts in the location of opportunities for MVTs over time. Hence, the understanding obtained from Chapter 6 about MVT occurrences over space and time is a fundamental step for modelling MVT in this Chapter 7.

This chapter builds on the work of Chapters 5 and 6 to examine in depth the factors that influence MVT during the four periods of the day in Riyadh. The theoretical frameworks developed in RAT, CPT and an integrated version of these theories will be used to do this. This chapter will mainly report the results of the regression models described in Chapter 5, and the interpretation and discussion of the findings will be presented in Chapter 8. The chapter is divided into four sections, as follows. Section 7.2 examines the elements for RAT, highlighting the results of the OLS and ML regression models. Section 7.3 concentrates on the results of the OLS and ML regression models for MVT, using the elements that represent CPT. Section 7.4 attempts to present the results of the OLS, GWR and ML regression models based on factors derived from the integration of the theories (RAT and CPT). The final Section 7.5 summarises the main results.

7.2 MVT and RAT

In this section, the results obtained from the OLS and ML regression analysis are based on the variables for measuring the elements of the RAT. Nineteen variables that were presented in Section 5.3.3. to represent RAT's themes: motivated offenders, suitable targets and absence of capable guardians (Cohen and Felson, 1979). The following sections attempt to present the significant predictors, starting with the original variables, and then using those based on the PCA components produced in Chapter 5, Section 5.4.2.2. This strategy helps us to understand how every variable can help contribute to predicting the MVT during each period. The four periods are as follows: Period One (12 am to 6 am), Period Two (6 am to 12 pm), Period Three (12 pm to 6 pm) and Period Four (6 pm to 12 am). To our knowledge, no research has been done to model MVT under environmental criminology during different times of day. Existing MVT studies, which were reviewed in Chapter 4, have treated explanatory variables as though they have consistent effects on MVT throughout the day.

Following this, a ML regression analysis based on the PCA was conducted in order to predict the probability of MVT occurrences during four time periods under RAT (Section 7.2.2). The ML has been used in regression models in the criminology field (Andresen, 2015; Andresen and Jenion, 2004; Peng and Nichols, 2003).

7.2.1 Results of the OLS Regression Model

The OLS regression method has been used to examine RAT variables in previous studies (Rice and Smith, 2002; Copes, 1999). In the following subsections, the OLS regression models were run with the original variables representing RAT, then with the PCA components representing these variables.

7.2.1.1 The Original Variables

In Table 7-1, amongst the 19 variables representing the themes of RAT, very few of the variables contributed to predicting motor vehicle theft (MVT) rates throughout the day. The adjusted R-squared values for the four regression models in Table 7-1 indicate that the regression model for Period Two (6 am to 12 pm) explained more of the variance in the MVT rates using the current predictor variables than the other periods' models did. The adjusted R-squared indicates that nearly 60% of the variance in the MVT rates was explained for Period Two. Interestingly, although Period Four (6 pm to 12 am) accounted for the highest frequency of MVT incidents, the

OLS regression model for MVT rates during Period Four exhibited a lower adjusted R-squared value (0.53) than Period Two (6 am to 12 pm) did.

Table 7-1: Estimated coefficients for variables in the OLS regression models

Variables	**Period One (12 am – 6 am)**		**Period Two (6 am – 12 pm)**		**Period Three (12 pm – 6 pm)**		**Period Four (6 pm – 12 am)**	
	Beta	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
Age 15-24	====	==	-0.299	0.000	==	==	-0.229	0.003
Non-SA males	0.231	0.001	0.343	0.000	0.433	0.00	0.446	0.000
Employed FE	-0.188	0.007	-0.38	0.000	-0.367	0.00	-0.348	0.000
Single	=====	===	0.248	0.000	==	==	0.246	0.001
Diversity	===	===	-0.152	0.010	==	==	==	===
LNEQ	0.422	0.000	==	===	==	==	==	==
Adjusted R^2	0.45		0.59		0.44		0.53	
Durbin-Watson statistic	1.74		1.71		1.75		1.587	

The result of the OLS regression in Table 7-1 shows that the percentage of young males in the population aged between 15 and 24 contributed negatively to predicting the MVT rates during Period Two (6 am to 12 pm) and Period Four (6 pm to 12 am). The standardised values of the effect size 'beta' were -0.29 and -0.22 for Period Two and Four respectively, with P-values < 0.01 (Table 7-1). This variable did not significantly contribute to predicting MVT rates during Periods One and Three. Furthermore, the results from the OLS regression model indicate that the percentage of single people contributed positively to predicting MVT rates during only Period Two (work hours) and Period Four (evening). The value of the coefficient for Period Two was 0.248 and P-value = 0.000, while for Period Four, the beta = 0.246 and P-value = 0.001. However, the results of the correlation matrix in Table 7-2 show that the percentage of single people only had a significant positive correlation with MVT rates during Period One (0.164).

What stands out in Table 7-1 above, the percentage of people with LNEQ showed a significant positive influence on MVT rates during only Period One (beta = 0.422; P-value < 0.01). This variable had no significant effect on predicting MVT rates during Periods Two, Three and Four. It is apparent from Table 7-2 showing the correlation matrix below that the LNEQ had the greatest significant positive correlation with MVT rates during Period One. Moreover, the beta values for the predictors for MVT rates during Period One illustrate that the LNEQ was the most significant contributor in predicting MVT rates during Period One. Here, in this study, the LNEQ was used to measure poverty in Riyadh's neighbourhoods. The results indicate that LNEQ predicted MVT rates only during Period One. Overall, then, it can be seen that there is considerable variation in the effects of the predictors across the different time periods of the day, highlighting the deficiencies of previous MVT studies that treated variables as having consistent effects throughout the day.

The results obtained from the regression model in Table 7-1 reveal that the percentage of non-Saudi people had significant positive effect on MVT rates throughout the day. In addition, it had the strongest effect on MVT rates during Period Four. The beta values were 0.23, 0.34, 0.43 and 0.44 for Periods One, Two, Three and Four, respectively, with p values < 0.01 (Table 7-1). The most surprising aspect of the results is that the percentage of employed females showed a significant negative influence on MVT rates during the four time periods. This is in contrast to the hypothesis formulated in Chapter 5, that the increase of the proportion of females employed in the neighbourhood would positively affect MVT occurrences. This could be attributed to the different context of SA and the nature of MVT, which will be discussed in Chapter 8.

Finally, a number of variables had a significant association with the MVT rates, such as average family size and percentage of households with no vehicles, Table 7-2. However, when they were included with the other predictors in the multiple linear regression, they made no significant contribution in terms of predicting MVT rates. This could be due to the presence of multicollinearity, as explained in Chapter 5. Thus, the next step is an OLS regression model based on PCA. PCA has been used in regression applications to overcome the multicollinearity and reduce the number of variables (Congdon, 2013; Willits et al., 2011; Morenoff and Sampson, 1997).

Table 7-2: Correlation matrix for the RAT variables and MVT rates

Variables	MVT 12 am-6 am	MVT 6 am -12 pm	MVT 12 pm- 6 pm	MVT 6 pm -12 am
Renters	-0.007	-0.048	-0.064	-0.05
Average of family size	-0.259**	-0.383**	-0.328**	-0.386**
Single	0.164*	0.018	0.033	0.024
LNEQ	0.620**	0.536**	0.475**	0.469**
Unemployment	0.072	0.056	0.012	0.002
Diversity	-0.358**	-0.412**	-0.345**	-0.357 **
Male population density	0.097	0.179*	0.169*	0.207**
HNV	0.351**	0.432**	0.455**	0.432**
Age 15_24	-0.168*	-0.310**	-0.291**	-0.286**
Employed females	-0.483**	-0.610**	-0.537**	-0.547**
Housewives	0.102	0.179*	0.203*	0.194*
Employed males	0.369**	0.483**	0.430**	0.478**
Students	-0.494**	-0.619**	-0.558	-0.591
Non-SA males	0.501*	604**	0.577**	0.629**
Roads A	-0.098	-0.143	-0.112	-0.054
Roads B	-0.025	0.063	0.114	0.146
Roads C	0.167*	0.260**	0.282**	0.309**
Roads D	-0.139	-0.171*	-0.105	-0.099
Roads E	0.019	0.086	0.112	0.143

***Correlation is significant at the 0.05 level/ ** correlation is significant at the 0.01 level**

7.2.1.2 The PCA Scores

The second set of OLS regression models are based on those PCA components reflecting the themes of RAT, which are illustrated in Section 5.4.2.2. The six components that were extracted include: PC1 – foreign workers, PC2 – high density of population and roads. PC3 – female employed with high diversity, PC4 – single and young people, PC5 – poverty level, PC6 – freeways A. From Table 7-3 below, we can see that the overall results for all the models are in agreement with the results from the OLS regression model based on the original variables. For example, the value of the adjusted R-squared (Table 7-3) shows that the explanatory power of the regression models for MVT rates was the highest for Period Two with a value of 0.56.

Table 7-3: Estimated coefficients for PC Scores in the OLS regression models.

Components	Period One (12 am – 6 am)		Period Two (6 am – 12 pm)		Period Three (12 pm – 6 pm)		Period Four (6 pm – 12 am)	
	Beta	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
PC1	0.50	0.000	0.57	0.000	0.52	0.000	0.55	0.000
PC2	==	===	==	==	==	==	0.15	0.009
PC3	-0.38	0.000	-0.46	0.000	-0.40	0.000	-0.39	0.000
PC4	0.22	0.000	==	==	==	==	==	==
PC5	0.18	0.002	0.10	0.046	==	==	==	==
PC6	===	==	-0.13	0.014	==	==	==	==
Adjusted R2	0.47		0.56		0.42		0.48	
Durbin-Watson statistic	1.72		1.70		1.64		1.529	

Table 7-3 above, shows that Component Four – PC4, which represents single people and young people, had a significant positive influence on the MVT rates during Period One, and its standardised coefficient was 0.22. This can be compared with the results of the correlation matrix (Table 7-4), which indicate that PC4 had a significant positive association with the MVT rates during Period One (r = 0.233), whereas it had no significant correlation with the MVT rates during the other periods. The significant effect of PC4 – single people and young people on the MVT rates appears to be in line with the results of the correlation matrix for the variables and the components. As indicated, the percentage of single people only had a significantly positive association with the MVT rates during Period One (Table 7-4), whereas the percentage of males aged from 15 to 24 had the lowest negative association with the MVT rates during Period One. The PCA suggests that the young males had a positive effect on MVT rates during the sleeping hours in areas where there was a high percentage of single people. Previous Western studies on MVT revealed contradictory findings on the association between MVT and the young population as reported to be positive (Roberts and Block, 2012) or negative (Copes, 1999) and to have no effect (Hannon and DeFronzo, 1998). This contradictory finding will be discussed in Chapter 8.

Another component that significantly predicted the MVT rates was PC5, which reflects poverty through the following indicators: the percentages of people with LNEQ, the unemployed and renters (see Chapter 5, Section 5.4.2.2 for more details). The results, as shown in Table 7-3, indicate that PC5 had a significant positive effect on MVT rates only during Period One and Period Two, with betas of 0.180 and 0.10, respectively. The poverty component moves in the same direction as the single people and young males component (PC4), which had a significant positive association with MVT rates only during Period One (0.18); it had no significant correlations with the other periods (Table 7-4). Vehicles in neighbourhoods characterised as poor or with high numbers of single and young males are more likely to be parked outside of houses during sleeping hours with poor security systems, and potential offenders often live nearby in these areas.

The coefficients in Table 7-3 indicate that the component – PC1, which reflects foreign workers, made a significant and positive contribution to predicting MVT rates throughout the day. The beta values for this factor during Periods One, Two, Three and Four were 0.50, 0.57, 0.52 and 0.55, respectively, with P-values < 0.01 (Table 7-3). This component accounted for the biggest contribution in predicting MVT rates during all periods, which is consistent with the results of the OLS regression in Table 7-1 in terms of the effect size of the percentage of non-Saudis on MVT rates.

Interestingly, as shown in Table 7-3, the component – PC2, which was highly correlated with the density of the male population and the density of roads, positively influenced MVT rates during Period Four (6 pm to 12 am), whereas it had no significant effect on MVT rates during Periods One, Two and Three. The standardised coefficient "beta" was 0.15 with a level of significance that was < 0.01. By looking at the correlation matrix (Table 7-2), we can see that the variables that reflect PC2 (the density of arterial roads classified as C and male density) exhibited a more significant positive association with MVT rates in Period Four than in the other time periods (Table 7-2). Furthermore, the results yielded from OLS regression and the correlation matrix (Table 7-3 and Table 7-4) show that the density of freeways and collector roads and the percentage of employed females had a negative effect on MVT rates throughout the day.

Table 7-4: Correlation matrix for the PCs with MVT rates

Components	MVT	MVT	MVT	MVT
	12 am – 6 am	6 am -12 pm	12 pm- 6 pm	6 pm -12 am
PC1	0.508**	0.579**	0.523**	0.558**
PC2	-0.008	0.069	0.116	0.153
PC3	-0.388**	-0.461**	-0.401**	-0.395**
PC4	0.223**	0.08	0.068	0.078
PC5	0.180*	0.106	0.065	0.045
PC6	-0.105	-0.132	-0.098	-0.051

Diagnostic of the Spatial Autocorrelation of the Residuals

As can be seen from Table 7-5 which shows Moran's I scores for the residuals, the residuals for the OLS regression models for predicting the MVT rates during Periods One and Two were random. This indicates that the residuals were not spatially correlated; hence, the assumptions for the OLS were met for both models. Meanwhile, the residuals for the OLS regression models for predicting the MVT rates during Periods Three and Four were clustered, which suggests a statistically existing spatial autocorrelation amongst residuals yielded from the OLS regression models. Existing spatial autocorrelations between residuals for OLS regression models were also diagnosed by other crime studies (Desmond et al., 2010; Chainey and Ratcliffe, 2005), whereas other researchers have found that the residuals were random (Wallace et al., 2006). However, to our knowledge, this is the first study that has found these variations in models' performances in explaining MVT rates at different periods of the day.

The results of diagnosing the spatial autocorrelation are strong evidence that the OLS regression performed well in predicting MVT rates during Periods One and Two using the factors that measured the themes of RAT. In contrast, the traditional regression model did not perform well in explaining the MVT rates during Periods Three and Four in some areas, where over-predictions and under-predictions were clustered. Overall, these clustered residuals could be an indication of missing key explanatory variables (Rosenshein et al., 2011), such as environmental features, that could help to explain the variations in MVT rates during Periods Three and Four. Therefore, the environmental variables that represent CPT themes will be examined in the following Section 7.3. Then, they will be integrated in a single regression model to determine if the performance of regression models improves.

Table 7-5: Global Moran's I for the regression residuals

Summary	Period One	Period Two	Period Three	Period Four
	12 am - 6 am	6 am -12 pm	12 pm- 6 pm	6 pm -12 am
Moran Index	0.0167	0.0217	0.0462	0.0498
z-scores	1.1856	1.449	2.706	2.888
Cluster/Random	Random	Random	Clustered	Clustered
p-values	0.235	0.147	0.006	0.0038

7.2.2 Results of the ML Regression Model

This analysis was conducted to identify the effects of the selected factors on the probability of MVT occurrences throughout the day. The results of the ML regression model are presented in Table 7-6. The logistic slope coefficients indicate that for one unit of change in every independent variable, the logit of MVT to occur during Period Two, Three and Four relative to Period One is expected to change by log-odds units when the other independent variables in the model are held constant. The predictors that significantly influenced the probability of MVT occurrence, with associated p-values less than 0.05, are shown in Table 7-6.

Table 7-6: Parameter estimates in the ML regression model

PCs	Period Two			Period Three			Period Four		
	B	Sig	Exp(B)	B	Sig	Exp(B)	B	Sig	Exp(B)
PC1	0.191	0.000	1.21	0.138	0.000	1.148	0.113	0.000	1.119
PC2	0.082	0.000	1.085	0.059	0.006	1.061	0.121	0.000	1.129
PC3	-0.119	0.000	0.887	-0.049	0.043	0.952	==	==	==
PC5	-0.047	0.017	0.954	-0.106	0.000	0.899	-0.133	0.000	0.876
PC6	-0.083	0.001	0.92	==	==	==	==	==	==
Model Fitting Information									
-2 Log likelihood	**Intercept Only**	3284.5	**AIC**	3025.68					
	Final	2983.6	**Sig**	0.000					

***The Reference Category is Period One**

Table 7-6 shows that PC5 (poverty) had the strongest influence on the probability of MVT occurrences during Period One. The results showed that if the score of PC5 in a neighbourhood increases by one unit, the multinomial log-odds of MVT occurrence during Periods Two, Three and Four to Period One would be expected to decrease by 0.047 units, 0.106 units and 0.133 units, respectively while all other variables in the model are constant. Thus, if the percentage of poverty increases in a neighbourhood, that neighbourhood would be more likely to have more MVT incidents during Period One than in the other periods.

The results of the ML regression model in Table 7-6 indicate that if the percentages of PC1 (foreign workers) in a neighbourhood increases by one unit, the multinomial log-odds of MVT occurrence during Period Two compared to Period One would be expected to increase by 0.191 units, while all other variables in the model are held constant. Moreover, the results showed that if the percentage of PC1 increases in a neighbourhood, that neighbourhood would be less likely to have MVT incidents during Period One relative to Period Two. The multinomial log-odds of MVT occurrences during Periods Three and Four to Period One would be expected to increase by 0.138

unit and 0.113 units respectively, while all other variables in the model are held constant. Overall, if two neighbourhoods have identical levels of predictor variables, the neighbourhood with the higher levels of PC1 (Foreign workers) would be more likely to have MVT incidents occur in Period Two than in the rest of the day and more incidents than a neighbourhood with a lower percentage of foreign workers (PC1).

Table 7-6 shows that the relative risk of MVT occurring during Period Two , Three and Four to Period Four would be expected to increase by factors of 1.085, 1.061 and 1.129, respectively, if PC2 (density of male population) increases in a neighbourhood by one unit while all other variables in the model are held constant. Consequently, the neighbourhood with a high density of PC2 was more likely to have more MVT incidents during Period Four than would a neighbourhood with a lower level of PC2, which represents a high density of population.

Furthermore, the results of the ML showed that if PC3 (female employed and diversity) in a neighbourhood increase by one unit, the multinomial log-odds of MVT occurrence during Periods Two and Three relative to Period One would be expected to decrease by 0.119 unit and 0.049, respectively, while all other variables in the model are held constant. Thus, if the percentages of female employed and diversity increase in a neighbourhood, that neighbourhood could to be more likely to have more MVT incidents during Period One than in Periods Two and Three.

7.2.3 Summary

It can be concluded that the results yielded from the ML model support the results from the OLS regression models. Both agreed that specific significant factors affected the occurrence of MVT during certain periods of the day. For example, the most interesting finding was that factors indicative of poverty had the greatest effect on the MVT during Period One (sleeping hours) compared to the other time periods. Furthermore, the results of both the OLS and ML regression models indicated that areas with high PC2 (density of male population) tend to experience more MVT incidents during Period Four (6 pm to 12 am), whereas high PC1 (foreign workers) was more likely to influence MVT during Period Two (working hours) than during the other time periods.

The regression models for MVT rates during Period Two offered a better explanation of the variance in the MVT rates with the RAT variables than did the other models. The overall pattern of the residuals for both OLS regression models for MVT rates during Periods One and Two suggested that the residuals showed more a normal distribution than in Periods Three and Four as can be seen from the Durbin Watson statistics in Table 7-3. This was confirmed by the result of testing the spatial autocorrelations for these residuals, which revealed that they were random (Table 7-5). However, the OLS regression diagnostic for the residuals revealed that the models for predicting MVT rates during Periods Three and Four were clustered, indicating a positive spatial autocorrelation among the residuals. This suggests missing key variables that were not accounted for in the models (Rosenshein et al., 2011), in particular for MVT rates during Periods Three and Four. Therefore, the following Section 7.3 examines the environmental variables based on the conceptions of CPT, in order to determine their influence on predicting MVT rates. Then, the two theories, RAT and CPT, are integrated, to get potentially better models Section 7.4.

7.3 MVT and CPT

This section presents the results from the OLS and ML regression models based on the independent variables, reflecting the main elements of CPT: activity nodes, crime generators and attractors (Brantingham, P.J. and Brantingham, 2008; Brantingham, P.L. and Brantingham, 1993b), which have been proposed according to the reviewed literature (see Chapter 4). As in the previous sections for RAT, the section begins by presenting the results for the models based on the original variables and then reveals the results from the regression analysis based on PCA components.

7.3.1 Result of the OLS Regression Model

7.3.1.1 The Original Variables

The outputs of the OLS regression models using the variables that represent the themes of CPT are illustrated in Table 7-7. The table presents the coefficients that significantly contributed to predicting MVT rates at a level of significance < 0.05. In addition, the regression models were able to explain nearly half of the spatial variations in the MVT rates throughout the day. However, the OLS model for MVT during Period One had the lowest adjusted R-squared (0.35), whereas the model for MVT rates during Period Two accounted for the highest adjusted R-squared explanation, which was 0.57.

Table 7-7: Coefficients for the CPT variables in OLS regression models

Variables	Period One (12 am – 6 am)		Period Two (6 am – 12 pm)		Period Three (12 pm – 6 pm)		Period Four (6 pm – 12 am)	
	Beta	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
Car Facilities	0.32	0.000	0.32	0.000	0.28	0.000	0.28	0.000
Apartments	0.42	0.000	0.45	0.000	0.44	0.000	0.42	0.000
Car Parks	0.24	0.001	0.32	0.000	0.36	0.000	0.29	0.000
Roads B	-0.16	0.023	==	==	==	==	==	==
Industrial use	==	==	0.174	0.002	0.132	0.024	0.137	0.024
Roads C	===	==	===	==	==	==	0.133	0.034
Adjusted R^2	0.35		0.57		0.54		0.51	
Durbin-Watson statistic	1.476		1.313		1.45		1.336	

From Table 7-7 above, it is clear that the density of car facilities and car parks and the percentage of apartment buildings consistently predicted MVT rates in the four time periods. However, the percentage of apartment buildings made the greatest contribution in predicting MVT rates throughout the day. The effect sizes for this variable on the MVT rates during Periods One, Two, Three and Four were 0.42, 0.45, 0.44 and 0.42, respectively, with P-values < 0.01. Meanwhile, the density of car facilities had its biggest effect on the MVT rates during Periods One and Two, with beta values of 0.32 and 0.32, respectively. Furthermore, the greatest effect for the density of car parks on MVT rates was during Periods Two and Three, with Beta values of 0.32 and 0.36, respectively.

Table 7-7 above illustrates that areas which tended to have more industrial use positively influenced MVT rates during Periods Two, Three and Four, and the values of the effect were 0.17 (P-value = 0.002), 0.13 (P-value = 0.024) and 0.13 (P-value = 0.024) respectively. The correlation matrix in Table 7-8 indicates that the percentage of industrial land use had a moderately significant correlation with the MVT rates during the daytime periods (Periods Two and Three). Furthermore, in this study, road density was used to represent places that attracted vehicles from different places (see the data and methodology Chapter 5). Hence, it can be seen from Table 7-7 above that the density of major roads classified as B had a significant negative effect on MVT rates during Period One and made no significant contribution to predicting MVT rates during Periods Two, Three and Four. By way of illustration, the correlation matrix (Table 7-2) shows that the density of major roads classified as ‘B’ had a weak negative correlation with MVT rates during Period One, while it had a very weak positive correlation with the other periods. Conversely, from Table 7-7, the density of arterial roads classified as C had a significant positive effect on MVT rates during the evening (Period Four). The correlation matrix (Table 7-2) indicates that the density of arterial roads had its most significant positive correlation with MVT rates during Period Four, which was 0.3. This variation in the effects of different types of roads density on MVT rates during time periods of the day goes from having no effect during a certain period to predicting MVT rates during other periods. This finding is in contrast with findings of other studies (Suresh and Tewksbury, 2013; Lu, 2006; Copes, 1999), which did not take into account the variation through the day of the different types of roads when predicting MVT rates.

Table 7-8: Correlation matrix for the CPT variables with MVT rates

Variables	**MVT**	**MVT**	**MVT**	**MVT**
	12 am -6 am	**6 am -12 pm**	**12 pm- 6 pm**	**6 pm -12 am**
Recreational and entertainment	-0.043	-0.003	0.012	0.068
Industrial land use	0.184*	0.341**	0.308**	0.282**
Car Facilities	0.418**	0.459**	0.433**	0.398**
Car Park	0.408**	0.534**	0.544**	0.478**
Facilities	0.259**	0.336**	0.338**	0.349**
Residential areas	-0.334**	-0.433**	-0.412**	-0.378**
Apartment buildings	0.327**	0.441**	0.432**	0.469**
Commercial areas	-0.03	-0.03	0.06	0.059

7.3.1.2 The PCA Scores

The OLS regression results that appear in Table 7-9 are based on the principal component analysis centred on the themes of CPT. As shown in Table 7-9, the OLS model for predicting MVT rates during Period One performed worse than the other models. The adjusted R-squared of 0.27 indicates that the model only explained 27% of the variation in the MVT rates during the sleeping hours. In addition, the Durbin Watson statistic for this model showed a value of 1.217, which, while statistically acceptable, was also close to “1”, which was a cause of concern in terms of an existing positive correlation among the residuals.

Table 7-9: Estimated coefficients for PC scores in OLS regression models

Components	Period One (12 am – 6 am)		Period Two (6 am – 12 pm)		Period Three (12 pm – 6 pm)		Period Four (6 pm – 12 am)	
	Beta	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**	**Beta**	**Sig**
PC1	0.20	0.004	0.31	0.000	0.32	0.000	0.35	0.000
PC2	-0.32	0.000	-0.44	0.000	-0.38	0.000	-0.35	0.000
PC3	0.38	0.000	0.44	0.000	0.43	0.000	0.35	0.000
PC4	==	===	==	===	0.14	0.018	0.17	0.004
Adjusted R^2	0.27		0.48		0.45		0.40	
Durbin-Watson statistic	1.217		1.365		1.348		1.32	

The results of the multiple regression models in Table 7-9 indicate that PC1, PC2 and PC3 had consistent effects on the MVT rates during all periods. PC1, which refers to the high density of facilities and the percentage of apartment buildings, had a positive effect on MVT rates throughout the day, and it had its biggest effect on MVT rates during Period Four. The beta value was 0.35 (P-value < 0.01). PC2, which represents residential areas and collector roads classified as ‘D’, negatively contributed to predicting MVT rates during all periods. This is an interesting finding, as the Western studies found that residential areas tend to show a high concentration of MVT near victims' homes (Tonry, 2011; Higgins, N. et al., 2009; Jetmore, 2007; McCormick et al., 2007; Weisel et al., 2006; U.S. Department of Justice, 2000; Fleming et al., 1994; Clarke, R.V. and Mayhew, 1994; Harlow, 1988). The component – PC3, the density of car facilities and car parks, had a positive influence on MVT rates throughout the day, with the greatest contribution coming during the daytime periods (from 6 am to 6 pm).

What stands out in Table 7-9 is that PC4, which reflects areas classified for recreation and entertainment and for commercial use, only affected MVT rates during Periods Three and Four, with beta values of 0.14 (P-value = 0.018) and 0.17 (P-value = 0.004), respectively. Interestingly, as seen in the correlation matrix above in Table 7-8, both variables (recreational land use and commercial areas) showed weak positive correlations with MVT rates during Periods Three and Four, whereas they had weak negative correlations with MVT rates during Periods One and Two. The PC4, which reflects both variables, only had a significant positive correlation with MVT rates during the evening (Period Four; Table 7-10). The influence of mixed land use for recreational and commercial purposes on MVT rates during the evening corroborates the ideas of CPT, which suggests that node activities attract more potential offenders and victims at certain times, leading to increased opportunities for crimes to occur (Brantingham, P.L. et al., 2011; 2008; 1993).

Table 7-10: Correlations between MVT rates and the PCs

Components	**MVT**	**MVT**	**MVT**	**MVT**
	12 am – 6 am	**6 am -12 pm**	**12 pm- 6 pm**	**6 pm -12 am**
PC1	0.201*	0.310**	0.328**	0.357**
PC2	-0.323**	-0.443**	-0.380**	-0.359**
PC3	0.380**	0.447**	0.439**	0.358**
PC4	0.041	0.08	0.142	0.179*

Diagnostic of the Spatial Autocorrelation

Table 7-11 shows that the residuals for all the regression models were clustered, which indicates there exists significant positive spatial autocorrelations between the residuals. This suggests that the models did not perform well across the study area. As previously mentioned, existing spatial autocorrelation between the residuals can indicate that important explanatory variables were not included in the OLS model

(Rosenshein et al., 2011). This is likely a result of the absence of socioeconomic and demographic variables from the regression models. Therefore, in Section 7.4, the factors that were used to measure the RAT and CPT were integrated to improve the models' predictions of MVT rates during the four time periods.

Table 7-11: Global Moran's I for the regression residuals

Summary	Period One	Period Two	Period Three	Period Four
	12 am - 6 am	6 am -12 pm	12 pm- 6 pm	6 pm -12 am
Moran Index	0.08600	0.0778	0.0567	0.0822
Z-scores	4.769	4.337	3.241	4.550
Cluster/Random	Clustered	Clustered	Clustered	Clustered
P-values	0.000	0.000	0.0011	0.0000

7.3.2 Results of the ML Regression Model

The aim of this analysis is to determine the impact of the environmental components on the probability of MVT occurrence throughout the day based on the CPT themes. The model fitting information in Table 7-12 indicates that the full model predicts the MVT significantly better than the intercept model alone, with a P-value < 0.01. Moreover, Table 7-12 illustrates the odds ratios for the predictors, the exponentiation of the coefficient Exp(B), which can be interpreted as follows. Here, we used Period One as the reference category. The relative risk of MVT occurring during Periods Two, Three and Four relative to Period One would be expected to increase by a factor of 1.150, 1.103 and 1.136 respectively if the PC1 reflecting the density of facilities and roads in a neighbourhood increases by one unit while the other components in the model are held constant. Thus, if the percentage of PC1 increases in a neighbourhood, that neighbourhood would be more likely to have more MVT incidents during Period Two than in the other periods.

Furthermore, the neighbourhoods that tend to be residential (PC2) were more likely to have MVT incidents in Period One than in Period Two in comparison to neighbourhoods with less residential use. Interestingly, as shown in Table 7-12, if PC3, which reflects density of car facilities and car parks, increased by one unit, the multinomial log-odds of MVT occurrence during Periods Two, Three and Four relative to Period One would be expected to increase by 0.171 unit, 0.134 unit and 0.06 respectively, while all other components in the model are held constant. This result is in agreement with the results of the OLS regression that PC3 had its greatest effect on MVT rates during Periods Two. The result shows that areas with higher densities of car facilities and car parks have a higher probability of MVT occurrences during Period Two than in the other time periods.

The coefficients shown in Table 7-12 indicate that if PC4 (recreational activities and commercial land use) in a neighbourhood increases by one percentage, the multinomial log-odds of MVT occurrence during Period Three and Four relative to Period One would be expected to increase by 0.144 and 0.135 units, respectively, when holding all other variables in the model are held constant. The results suggest that areas with a high density of recreational and commercial activities were more likely to have more MVT incidents during Period Three than in the other periods.

Table 7-12. Estimated coefficients in the ML regression model

PCs	**Period Two**			**Period Three**			**Period Four**		
	B	**Sig**	**Exp(B)**	**B**	**Sig**	**Exp(B)**	**B**	**Sig**	**Exp(B)**
PC1	0.139	0.000	1.150	0.098	0.000	1.103	0.127	0.000	1.136
PC2	-0.068	0.003	0.934	==	==	==	==	==	==
PC3	0.171	0.000	1.186	0.134	0.000	1.144	0.06	0.009	1.061
PC4	==	==	==	0.144	0.000	1.155	0.135	0.000	1.145
Model Fitting Information									

-2 Log likelihood	**Intercept Only**	3284.5	**AIC**	3082.113
	Final	3052.113	**Sig**	0.000

***The reference category is Period One**

7.3.3 Summary

A comparison of the results from the OLS and the ML regression models reveals that the density of car facilities and car parks (PC3) had the most significant positive effect on MVT during Period Two, whereas the density of facilities and roads had its largest influence on the probability of MVT during Periods Two and Four. Moreover, areas with high recreational and commercial land use were more likely to have MVT occurrences during Periods Three and Four.

The environmental features that were used to measure CPT had a smaller effect on MVT rates during Period One (sleeping hours) than during the other time periods. Moreover, the examination of spatial autocorrelations among the residuals for the OLS regression models for predicting MVT rates during all periods revealed that the models were misspecified, which was likely as a result of missing the socioeconomic and demographic variables. This does not indicate that the OLS estimates were biased (Bernasco and Elffers, 2010; Anselin, 2001) but suggests that the built environments alone were not enough to explain the MVT rates. The following section attempts to address this limitation by integrating the CPT with the RAT.

7.4 Integration of the RAT and CPT Models

This analysis was conducted to integrate the RAT and the CPT variables in a single model in order to improve modelling MVTs. In our knowledge, this is the first attempt to integrate theory-informed socioeconomic, demographic and environmental variables in a regression model to predict MVT. Due to the high multicollinearity among the variables in this model, as explained in the Chapter 5, here the regression models were only based on the PCs. Eight components were extracted from the PCA to represent the selected 27 variables (see Chapter 5, Section 5.4.2.2).

7.4.1 Results of the OLS Regression Model

From Table 7-13, it is clear that the adjusted R-squared for the integration of theories performed very well relative to the previous regression models in predicting the MVT rates during all periods. For example, the results show that the regression model for MVT during Period Two explained 64% of the total variation in the MVT rates, whereas the OLS model based the RAT variables explained 56% of the variations in the MVT rates during the same period.

Table 7-13: Estimated coefficients in OLS regression integration models

Components	Period One (12 am – 6 am)		Period Two (6 am – 12 pm)		Period Three (12 pm – 6 pm)		Period Four (6 pm – 12 am)	
	Beta	Sig	Beta	Sig	Beta	Sig	Beta	Sig
PC1	0.485	0.000	0.593	0.000	0.552	0.000	0.569	0.000
PC2	===	===	0.108	0.025	0.137	0.012	0.178	0.001
PC3	-0.338	0.000	-0.427	0.000	-0.369	0.000	-0.351	0.000
PC4	0.367	0.000	0.255	0.000	0.258	0.000	0.252	0.000
PC5	0.179	0.002	0.111	0.021	===	===	===	===
PC7	==	==	===	===	===	====	0.111	0.042
PC8	-0.114	0.044	-0.194	0.000	-0.176	0.001	===	===
Adjusted R^2	0.51		0.64		0.54		0.54	
Durbin-Watson statistic	1.75		1.70		1.56		1.41	

By looking at the coefficients in Table 7-13, PC1 (foreign workers) accounted for the biggest contribution amongst the components in predicting MVT rates throughout the day. The beta values for this factor were 0.48, 0.59, 0.55 and 0.56, respectively, for Periods One, Two, Three and Four, with P-values < 0.001. Furthermore, PC2 (the density of the male population and the density of facilities) had a significant effect on MVT rates during Periods Three and Four, with its greatest effect on MVT rates during Period Four, while the standardised coefficients were 0.13 and 0.17, respectively. The correlation matrix (Table 7-14) shows that PC2 only had a significantly positive association with MVT rates during Period Four (r = 0.17).

From Table 7-13, PC4 (single people, males aged between 15 and 24) had a significant positive influence on the MVT rates during all periods, with its greatest effect during Period One (sleeping hours) (beta = 0.36, P-value < 0.001). Moreover, the result of the OLS regression in the table below shows that PC5 – (poverty) contributed positively to predicting MVT rates during Periods One and Two, with the largest effect size during Period One, and with beta values of 0.17 (P-value = 0.002) and 0.11 (P-value = 0.021), respectively. The correlation matrix (Table 7-14) shows that PC5 only had a significant positive correlation with MVT rates during Period One (Pearson Correlation =0.17). Interestingly, PC7, which represents recreational and entertainment areas, only had a statistically significant effect on MVT rates during Period Four. The beta value was 0.11 (P-value = 0.042). Contrary to the expectation under RAT that 'housewives' can work as capable guardians in houses (Felson, 1986), the PC6 indicated that housewives had no significant effect on predicting MVT rates during all periods of the day, and the variable of the percentage of housewives actually had a significant positive correlation with MVT rates. However, as was mentioned in Chapter 4, because of houses' architecture in SA, housewives are most likely to have no role to act as capable guardians in protecting vehicles outside of houses.

Table 7-14: Correlation matrix for the components representing the integrated theories

Components	MVT	MVT	MVT	MVT
	12 am - 6 am	6 am -12 pm	12 pm- 6 pm	6 pm -12 am
PC1	0.485**	0.593**	0.552**	0.569**
PC2	0.047	0.108	0.137	0.178*
PC3	-0.338**	-0.427**	-0.369**	-0.351**
PC4	0.367**	0.255**	0.258**	0.252**
PC5	0.179*	0.111	0.049	0.041
PC6	-0.006	-0.083	-0.034	-0.024
PC7	0.005	0.05	0.077	0.111
PC8	-0.114	-0.194*	-0.176	-0.098

Diagnostic of the Spatial Autocorrelation

The spatial autocorrelation of the residuals for the OLS were checked to see if there were any violations of the assumptions (Charlton and Fotheringham, 2009; Ceccato, 2009; Desmond et al., 2010; Chainey and Ratcliffe, 2005). It can be seen from the results for the Moran's index below in Table 7-15 that the residuals of the OLS regression models for the MVT rates during Periods One, Two and Three were random, which means that no spatial autocorrelation exists. In contrast, the residuals for the OLS regression models for the MVT rates during Period Four were spatially clustered. This significant positive spatial autocorrelation in the OLS regression residuals for Period Four might suggest that the model is misspecified.

Table 7-15: Global Moran's I for the regression residuals

Summary	Period One	Period Two	Period Three	Period Four
	12 am - 6 am	**6 am -12 pm**	**12 pm- 6 pm**	**6 pm -12 am**
Moran Index	0.0147	0.019	0.021	0.065
Z-scores	1.08	1.34	1.43	3.66
Cluster/Random	Random	Random	Random	Clustered
P-values	0.277	0.177	0.150	0.000249

In order to identify where there are over- and under-predictions for the OLS regression model for MVT rates during Period Four, the residuals are mapped in Figure 7-1 below, which shows that the high positive residuals tended to cluster heavily in the eastern areas of Riyadh. This suggests that the explanatory variables did not adequately produce the best linear regression model for predicting MVT rates during Period Four within these eastern areas. Future research would be useful to find out other key variables that can work well in explaining MVT rates during Period Four, particularly in the eastern areas of the city.

Spatial models, such as GWR, take into account the presence of the existing spatial autocorrelation. Hence, the following section outlines the results of a GWR analysis

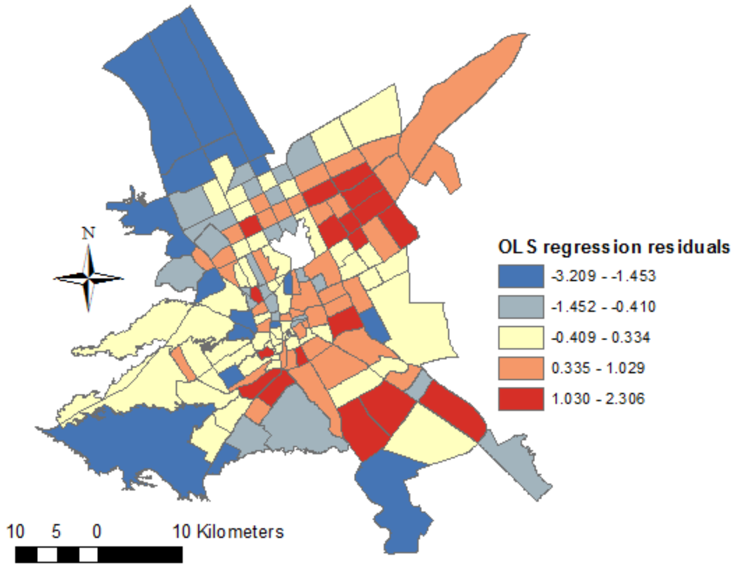


Figure 7-1: OLS regression residuals during Period Four

7.4.2 Results of the GWR

In this analysis, GWR was used to handle the problem of the existing spatial autocorrelation in the residuals from OLS regression model (for Period Four as shown in Table 7-15). It was also used to determine the local predictive power of the regression models and where the effect of predictors changes in terms of their effects on MVT rates from one neighbourhood to another across the study area – spatial heterogeneity. Thus, it allows us to see where the model performs well and where it does not. This will help to determine the places that are priorities for implementing crime prevention strategies (see Chapter 9).

GWR is very sensitive to multicollinearity among predictors. Therefore, the GWR model was based on the PCA. Hence, a set of significant components, which represent the integrated theories, were used in the final OLS regression model. Table 7-16 provides the results obtained from the GWR models. It can be seen that the explanatory power of the regression models improved. For example, the GWR model explained about 70% of the variation in MVT rates during Period Two, while the earlier OLS model for the same period explained 64% of the variation. Interestingly, the GWR model's performance in predicting MVT rates during Period Four showed considerable better performance relative to the OLS regression model for the same period. The OLS regression model explained 54% of the variation for MVT rates, whereas the GWR model explained 70% of the variation, which is an increase of 16%. This could be attributed to the fact that the issue of the spatial autocorrelation of the residuals of the OLS regression model was solved by the GWR. As presented in Table 7-17 below, the residuals for the GWR models were random. However, the AIC values for the GWR models for MVT rates during Periods One (−34.8) and Two (13.8) were lower than these values for the GWR models during Periods Three and Four, suggesting that the GWR models for Periods One and Two provided better fits to the observed data than other periods. This is also in line with the results from the OLS regression models, which indicated that the residuals for models during Periods One and Two tended to be more independent than the residuals for Periods Three and Four (see the values of Durbin–Watson in Table 7-13). This could be attributed to the fact that vehicles are more likely to be parked during Period One – sleeping hours – and also during Period Two – working hours, , whereas they tend to move around during Periods Three and Four. This point will be discussed in detail later in Chapter 8.

Table 7-16: Fitting information of the GWR models

Summary	**Period One**	**Period Two**	**Period Three**	**Period Four**
	12 am - 6 am	**6 am -12 pm**	**12 pm- 6 pm**	**6 pm -12 am**
Adjusted R^2	0.59	0.70	0.64	0.70
AIC	-34.8	13.8	76.2	67.3

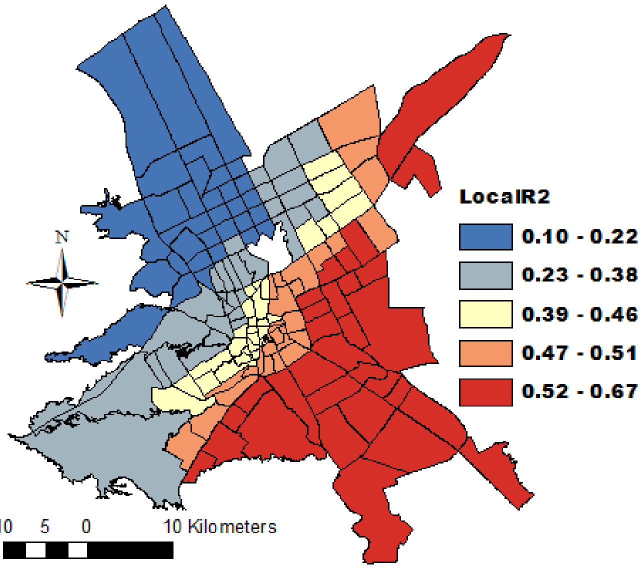
Table 7-17: Global Moran's I for the regression residuals from GWR models

Summary	**Period One**	**Period Two**	**Period Three**	**Period Four**
	12 am - 6 am	**6 am -12 pm**	**12 pm- 6 pm**	**6 pm -12 am**
Moran Index	-0.0152	-0.024	-0.011	-0.007
z-scores	-0.453	-0.923	-0.245	-0.063
Cluster/Random	Random	Random	Random	Random
P-values	0.65	0.355	0.80	0.94

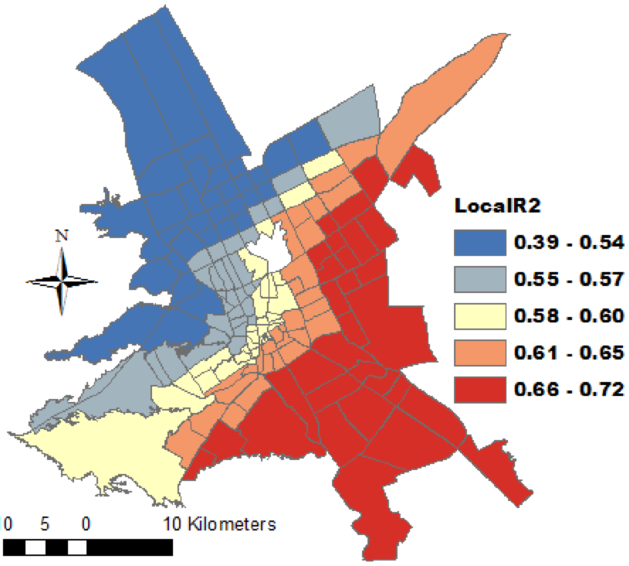
7.4.2.1 Mapping Local R^2

GWR provides information that show's model's performance across the study area. From the maps below (Figure 7-2), it is obvious that all models exhibited strong performance in the southern areas and in the southeast and southwest neighbourhoods of the city, while the worst performance of the models was in some of the northern districts for MVT rates during Periods One, Two and Three (Figures 7-2A, B and C). However, the performance of the model in predicting the MVT rates during Period Four showed a different performance than the other GWR models (Figure 7-2D). For example, the best performance for this model was in the southern areas and some central districts, whereas the worst was in the eastern and western areas. Furthermore, we can see that the GWR model for the MVT rates during Period Four (Figure 7-2D) had local R^2 ranging from an extremely low value of 0.09 (9%) to an extremely high R^2 value of 0.80 (80%), which indicates an unstable model.

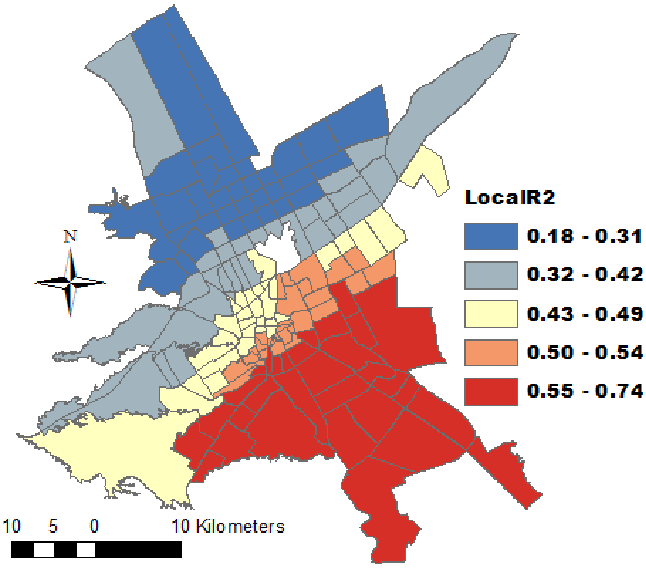
On the other hand, the GWR model for MVT rates during Period Two had a local R2 that ranged from 0.39 (39%) to 0.72 (72%), which indicates a more stable model (Figure 7-2A). In addition, the worst performance for the regression models for MVT rates during Periods One, Two and Three in the north were different than those during Period Four. Taken together, these results suggest two important findings. First, the spatial patterns of MVT during Period Four were significantly different from the patterns in the other time periods (Figure 7-2). Second, the factors responsible for these patterns appear to be different, at least in those areas where the performance for the model exhibited the less/worst explanations. Overall, this result supports the findings from the spatial point pattern test in Chapter 6, which indicated that the spatial patterns of MVT occurrences in Period Four were significantly different from the other periods, particularly in the eastern districts.



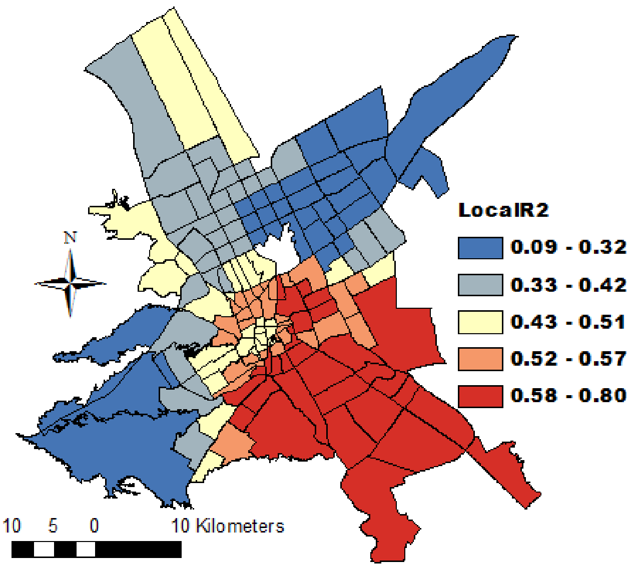
A. Local R^2 for Period One



B. Local R^2 for Period Two



C. Local R^2 for Period Three



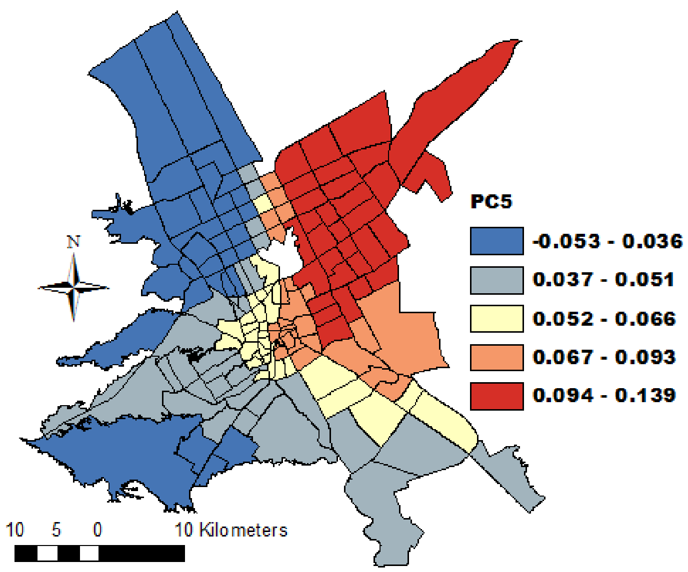
D. Local R^2 for Period Four

Figure 7-2: Variations in the models' performances throughout the day and across the study area, Riyadh

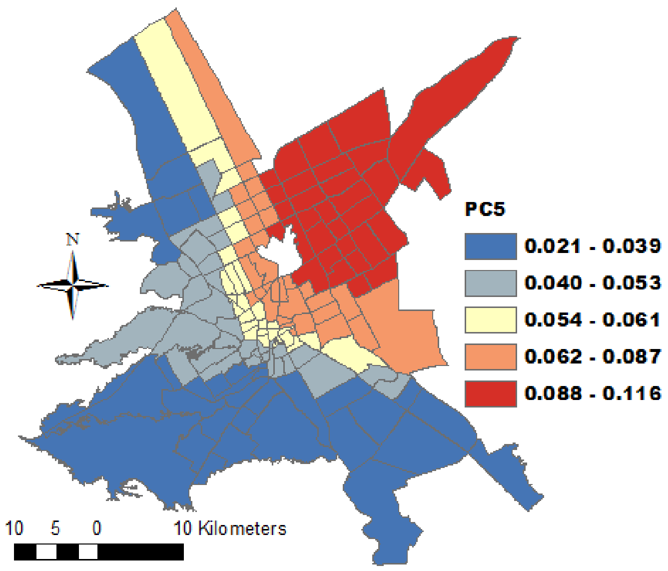
7.4.2.2 The Influence of the Coefficients on the Predictor Variables

Variations in the performance of the regression models across the study area occur because the influence of every predictor varies from area to area over the study area. Consequently, as seen in Figure 7-3, PC5 (Poverty) was a strong predictor of MVT rates during Periods One and Two in the eastern and north-eastern neighbourhoods. The areas highlighted in red denote neighbourhoods with positive coefficients for poverty. The map in Figure 7-3A indicates the highest positive effects on the MVT rates are during Period One, which were expected to increase by 0.13 when the poverty component increases by one point, while the biggest contribution of PC5 on the MVT rates during Period Two was an expected increase of 0.11 (see Figure 7-3B).

On the other hand, in some northern and western district locations, as highlighted in blue, poverty had a very low positive effect on MVT rates during Periods One and Two. For example, the lowest positive effects indicated that MVT rates during Period One were expected to increase by 0.005 when poverty increases by one. For the MVT rates during Period One, the relationship between poverty and MVT rates was positive in the majority of neighbourhoods, whereas only a few parts of the northern areas showed this factor having a negative relationship with MVT rates (Figure 7-3A). Meanwhile, the map in Figure 7-3B shows that PC5 had a consistent positive effect on MVT rates during Period Two in all areas of the city. This is an important feature of the GWR that allows for the independent variables to have a non-stationary relationship with the MVT rates, something that was not possible using the global regression model (OLS).



A. Effects of PC5 on MVT rates during Period One

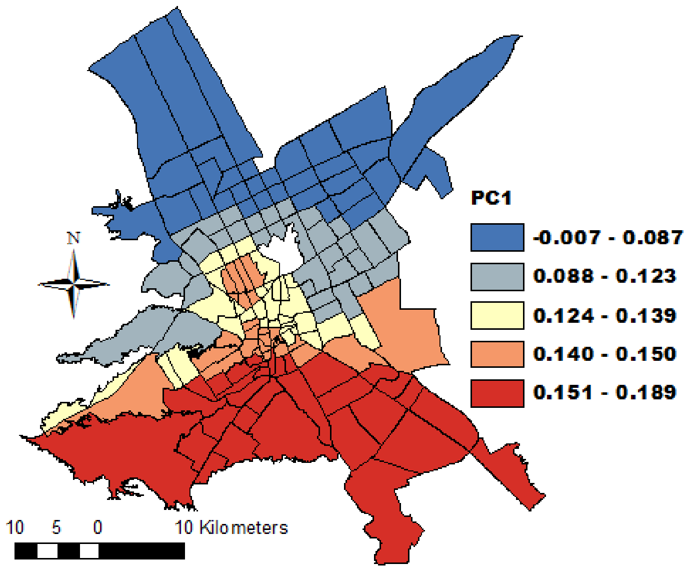


B. Effects of PC5 on MVT rates during Period Two

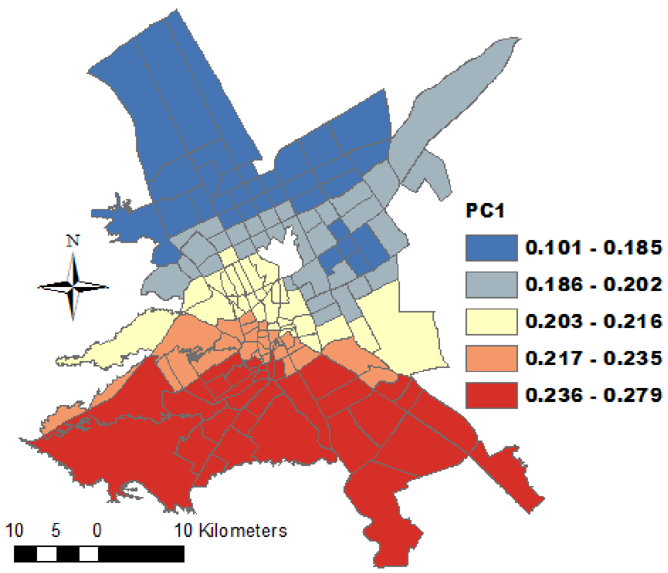
Figure 7-3: Effects of PC5 on MVT rates during Periods One and Two and across the study area, Riyadh

PC1 (foreign workers) was the strongest predictor for the MVT rates during all periods of the day, as shown in Table 7-13 (OLS model). By looking at the maps presenting the coefficients of PC1 that resulted from the GWR models, the effect of this component on the MVT rates can be compared throughout the day. In Figure 7-4 below, the red areas indicate locations where PC1 had a strong effect on MVT rates; these areas were mostly located in neighbourhoods in the south of Riyadh and in some parts of central districts. The very dark blue areas indicate locations where PC1 had a very weak relationship with MVT rates. However, the most interesting result to emerge here is that the coefficients for PC1 showed the strongest positive effect on MVT rates during Period Four in the northern and southern neighbourhoods, and these are highlighted in red (Figure 7-4D).

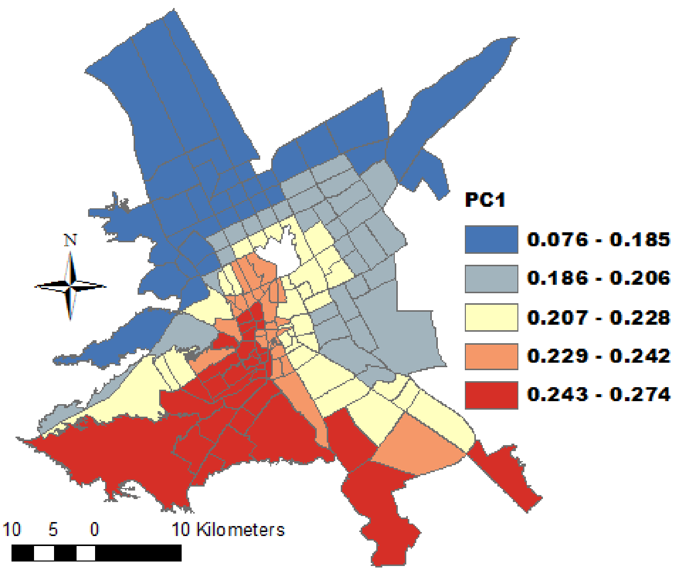
Overall, PC1 had a consistent positive effect on the MVT rates during Period Two, relative to the other time periods, across the study area (Figure 7-4B). The values of the coefficients for this component during Period Two ranged from 0.1 to 0.27 over the study area, whereas for Periods One and Four, they ranged between positive and negative relationships. This is in agreement with the results from both the OLS and ML regressions, which indicated that PC1 was the strongest predictor for MVT during Period Two. In addition, PC1 was the strongest in the southern areas, which appears to explain the results in Chapter 6, which showed that several southern neighbourhoods had high concentration of MVT rates throughout the day.



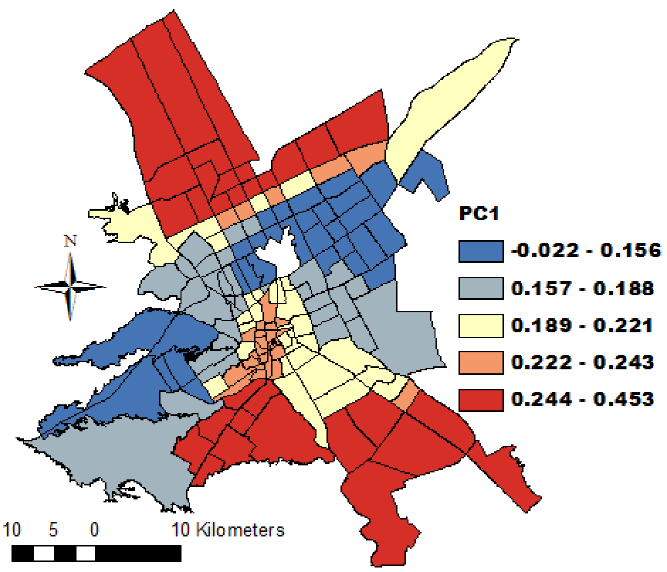
A. Effects of PC1 on MVT rates during Period One



B. Effects of PC1 on MVT rates during Period Two



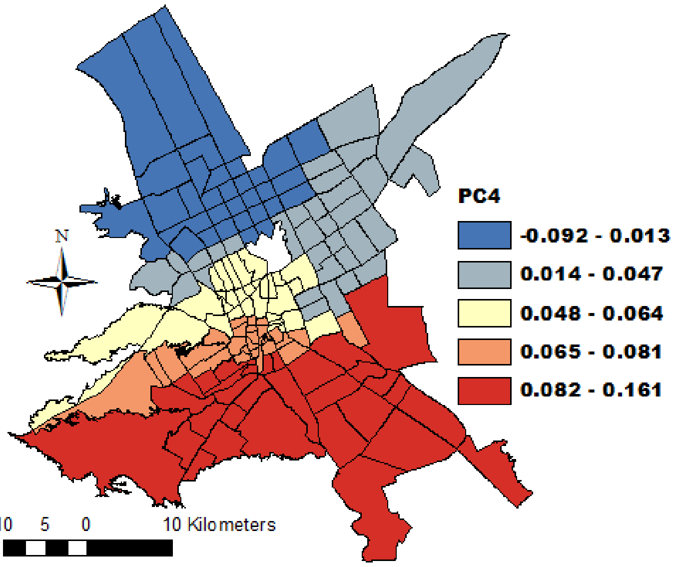
C. Effects of PC1 on MVT rates during Period Three



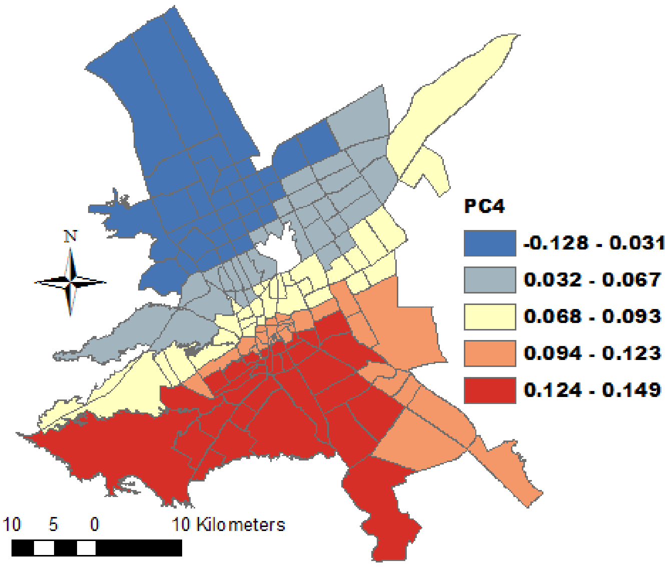
D. Effects of PC1 on MVT rates during Period Four

Figure 7-4: Effects of PC1 on MVT rates throughout the day and across the study area, Riyadh.

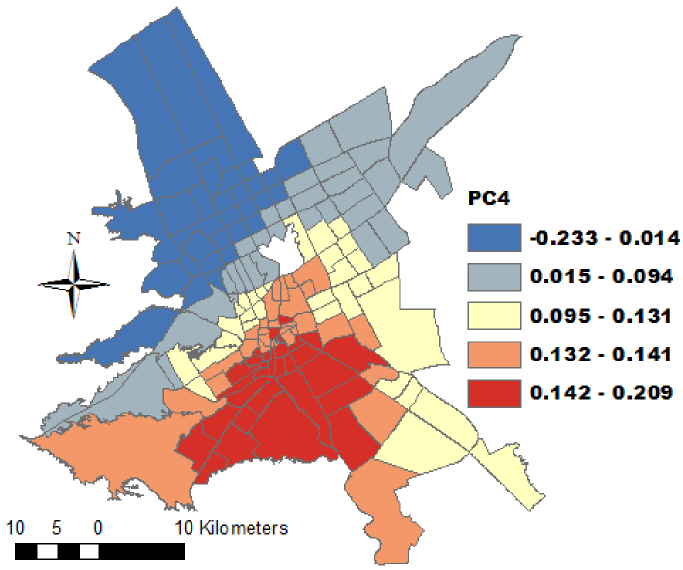
From the map (Figure 7-5), PC4 (single people and young males) had a consistent strong effect on MVT rates throughout the day in some parts of the southern and western neighbourhoods. The areas highlighted in red denote neighbourhoods with positive coefficients for PC4. Conversely, in some northern and western locations, highlighted in blue, PC4 had a very low negative effect on MVT rates. We can see that in a few parts of the northern areas, this factor negatively predicted MVT rates.



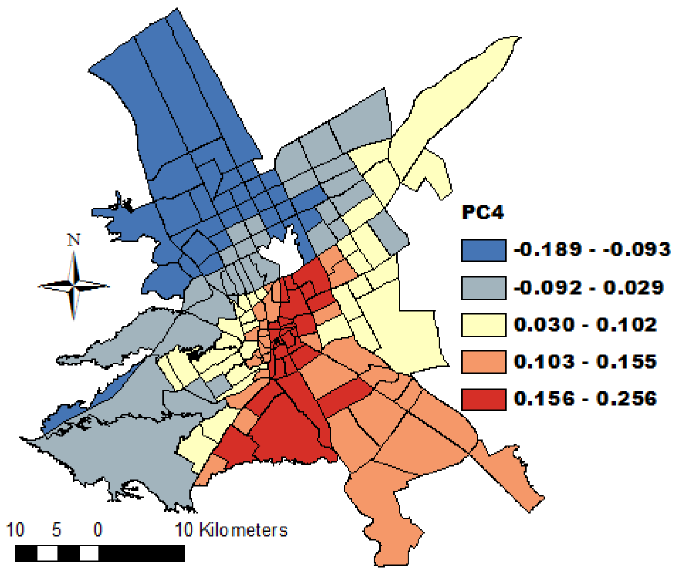
A. Effects of PC4 on MVT rates during Period One



B. Effects of PC4 on MVT rates during Period Two



C. Effects of PC4 on MVT rates during Period Three



D. Effects of PC4 on MVT rates during Period Four

Figure 7-5: Effects of PC4 on MVT rates throughout the day and across the study area, Riyadh

7.4.3 Results of the ML Regression Model

Having looked at the relationship between MVT rates and the predictors under the integration of the theories using the OLS regression models, and having explored this relationship at the local level using GWR, we now return to the global model using the ML regression model. The ML regression model was used to examine whether the integration of RAT with CPT could improve the explanation of MVT occurrences. As seen in Table 7-18, the Akaike information criterion (AIC) for the integrated model was the lowest (AIC = 3005.614) relative to the AICs for the separate ML models for the RAT (3025.68) and CPT (3082.113). This indicates that the ML model had a better fit after integrating the factors associated with RAT and CPT. Furthermore, Table 7-18 below illustrates the predictors that significantly contributed to predicting MVT occurrences, with associated P-values < 0.05. Here, we used Period One as the reference category.

Table 7-18: Estimated coefficients in the ML regression model

PCs	Period Two			Period Three			Period Four		
	B	**Sig**	**Exp(B)**	**B**	**Sig**	**Exp(B)**	**B**	**Sig**	**Exp(B)**
PC1	0.179	0.000	1.196	0.153	0.000	1.165	0.132	0.000	1.142
PC2	0.082	0.000	1.086	0.050	0.017	1.052	0.095	0.000	1.099
PC3	-0.115	0.000	0.891	-0.063	0.007	0.939	===	===	===
PC4	0.129	0.000	1.138	0.106	0.001	1.112	0.076	0.019	1.079
PC5	-0.054	0.011	0.947	-0.123	0.000	0.884	-0.151	0.00	0.860
PC7	0.053	0.045	1.055	0.099	0.000	1.104	0.081	0.001	1.084
PC8	-0.094	0.000	0.910	-0.051	0.035	0.950	===	===	===

Model Fitting Information				
-2 Log likelihood	**Intercept Only**	3284.501	**AIC**	3005.614
	Final	2957.614	**Sig**	0.000

***The Reference Category is Period One**

In Table 7-18, the coefficients show that if PC1 (foreign workers) in a neighbourhood increases by one unit, the multinomial log-odds of MVT occurrences during Periods Two, Three and Four to Period One would be expected to increase by 0.179, 0.153, 0.132 units respectively while the other variables in the model are held constant. This result indicates that if two neighbourhoods have identical levels of predictor variables, the neighbourhood with the higher percentage of the foreign workers (PC1) would be more likely to have MVT incidents occurring during Period Two relative to the other time periods than would a neighbourhood with a lower percentage of PC1.

Furthermore, by looking at Table 7-18, we can see that the relative risk for MVT to occur during Periods Two, Three and Four compared to Period One would be expected to increase by factors of 1.086, 1.052 and 1.099 respectively if the density of PC2 increases in a neighbourhood by one unit, given that the other variables in the model are held constant. Consequently, the neighbourhood with a higher PC2 would be more likely to have MVT incidents occurring during Period Four, relative to the other periods, than would a neighbourhood with a lower percentage of PC2.

The result of the ML regression model (Table 7-18) suggests that if the percentage of PC5 (poverty) in a neighbourhood increases by one unit, the multinomial log-odds of MVT occurrence from Periods Two, Three and Four relative to Period One would be expected to decrease by 0.054, 0.123 and 0.151 units, when holding all other variables in the model constant. Hence, if the percentage of PC5 (poverty) increases in a neighbourhood, we would expect this neighbourhood to be more likely to have MVT incidents in Period One (sleeping hours) relative to the other time periods Two, Three and Four. The coefficients shown in Table 7-18 indicate that if PC7 – (represents recreational and entertainment use) in a neighbourhood increases by one percentage, the multinomial log-odds of MVT occurrence during Periods Two, Three and Four relative to Period One would be expected to increase by 0.053, 0.099 and 0.081 units, respectively, when holding all other variables in the model constant. The results suggest that areas with a high density of recreational activities were more likely to have more MVT incidents during Period Three and Four than in the other periods.

7.4.4 Summary of the Integrated Model

The result of the regression models based on the integration of both theories suggest improvement in the model performances in predicting MVTs. The socioeconomic, demographic and environmental variables showed better representation of the variations in MVT occurrences over space and time. This result indicated that the significance for every variable was not constant, either throughout the day or across the study area. Furthermore, the OLS regression model based on the integrated factors for predicting the MVT rates during Period Four was misspecified. The diagnostic results for the residuals of the MVT rates during Period Four exhibited significant spatial autocorrelation, which suggests that a key variable could be missing from the regression analysis. The GWR model dealt with this misspecification, and the model's predicted MVT rates for Period Four were statistically valid.

The results indicate that neighbourhoods that tend to be poor were more likely to have MVT incidents during Period One (sleeping hours). PC1 (foreign workers) made the most significant contribution in predicting MVT rates during Period Two. Meanwhile, neighbourhoods with a high density male population and a high density of facilities tended to experience more MVT occurrences during Period Four. Furthermore, the results from the GWR suggest that the regression models performed very well in the southern areas, though they performed worse in predicting MVT rates in the northern areas for Periods One, Two and Three and in the eastern areas for Period Four. By way of illustration, the worst performance model in predicting MVT rates amongst the fourth GWR regression models can be seen during Period Four in the eastern areas. This finding is in agreement with the result of mapping the residuals of the OLS regression model during Period Four (Figure 7-1), which suggests that the explanatory variables did not work well in predicting MVT rates during Period Four in eastern areas. As indicated earlier, more work is needed to investigate variables that can provide better explanations for MVT rates within these areas.

7.5 Summary of Chapter 7

This chapter has presented models for MVT under RAT, CPT and an integration of the theories using regression models: OLS, ML and GWR. The chapter built his analysis on the findings of Chapter 6, in that the spatial patterns of MVT occurrences varied significantly from period to period throughout the day. Together, these results provide important insights into the occurrence of MVT in Riyadh and the applicability of Western environmental criminology. The results emphasize that certain factors contributed significantly to MVT rates in certain time periods, but show no significant at others. For example, during Period One (12 am to 6 am), the poverty factor had the greatest effect on MVT occurrences, while for Period Two (6 am to 12 pm), foreign workers made the largest contribution in predicting MVT. Moreover, areas with a high population density and high density of facilities experienced more MVT incidents during Period Four (6 pm to 12 am).

The OLS regression models indicate that the variables representing RAT were able to well explain MVT rates during Periods One and Two, but it did not well explain MVT rates during Periods Three and Four (Section 7.2.1). The results presented in the chapter indicate that OLS models based on CPT elements showed lower performance compared to the models based on the RAT themes (Section 7.3.1). The final Section 7.4 in this chapter modelled an integration of the two theories. The results show an improvement in the models' performance after integration of the variables associated with the two theories for MVT rates during Periods One, Two and Three. However, the OLS model predictions of MVT rates during Period Four failed to perform consistently well in explaining MVT rates due to the existing spatial autocorrelation. This violated the assumption of the OLS regression model. Thus, the GWR was used to overcome this issue and identify local predictive models across the study area – spatial heterogeneity. The overall results from the GWR identified that the relationships between the explanatory variables and the MVT rates were more likely to vary across location and time.

Overall, the results that were found in this chapter were notable, in that they showed that the influence of the examined factors on MVT varied significantly throughout the day. Furthermore, some of the findings yielded from the regression models were contrary to the hypotheses associated with RAT in Western studies. For example, the percentage of females employed had a negative effect and the percentage of housewives showed no significant effect on MVT rates. The next chapter will discuss the results of Chapter 7 in the context of the literature, the Saudi context and the existing knowledge about MVT.

Chapter 8

Discussion and Findings

8.1 Introduction

This study set out to understand motor vehicle theft (MVT) in Riyadh city under routine activity theory (RAT) and crime pattern theory (CPT). With this in mind, a number of objectives were achieved by exploring and detecting significant differences between the spatial patterns of MVT occurrence across the study area and during the four periods, and the results of these were presented in Chapter 6. Following this, the spatial relationships between MVT and socioeconomic, demographic and environmental features were investigated in Chapter 7 using RAT and CPT. A wide range of results from modelling MVT using regression methods were described in Chapter 7 in relation to their statistical significance in predicting MVT throughout the day. This chapter now links these results to the reviewed literature, theories and practice.

In order to achieve this, this chapter is divided into three sections. Sections 8.2 and 8.3 discuss the results of the analysis in relation to RAT and CPT, assessing their abilities to explain MVT throughout the day. As before, each day is divided into four periods: Period One (12 am to 6 am), Period Two (6 am. to 12 pm), Period Three (12 pm to 6 pm) and Period Four (6 pm. to 12 am). Section 8.4 discusses an integration of the two theories in terms of their performance and the findings yielded from the GWR. Section 8.5 provides a summary for the chapter. The recommendations and implications for research, policy and practice will be discussed in Chapter 9.

8.2 MVT and RAT

This section discusses the findings yielded from both the ordinary least squares (OLS) and multinomial logistic (ML) regression models presented in Chapter 7, particularly in Section 7.2, in understanding MVT from the theoretical framework developed under RAT. The following subsections discuss the results in relation to the influence of the factors that represent the core elements of RAT (Cohen and Felson, 1979). The section will begin in 8.2.1 by discussing the factors used to reflect motivated offenders in explaining MVT. Interpretations for factors representing the suitable target and the absence of capable guardians will be conducted in Sections 8.2.2

and 8.2.3, respectively. This section will conclude by providing a critical evaluation of the applicability of RAT to explain MVT in SA, in particular in Riyadh.

8.2.1 Motivated Offenders

Areas classified as poor tend to have a higher proportion of motivated offenders than other areas (Clarke, R.V., 1999; Copes, 1999; Messner and Blau, 1987). Furthermore, the findings of Al Angari (2002) suggest that car thieves' families often live in poverty in SA. Thus, the poverty level is likely to reflect the number of motivated offenders. The percentage of people with low or no educational qualifications (LNEQ) and experiencing high unemployment rates is used as an indication of poverty (see Section 5.3 in Chapter 5). The results of the analysis show that LNEQ only had a significantly positive influence on MVT rates during Period One, while unemployment rates showed no statistical significance in predicting MVT rates during any of the time periods (Table 7-1). Thus, this finding does not support previous findings suggesting that unemployment rates have a positive association with MVT rates in the U.S. (Roberts and Block, 2012; Hannon and DeFronzo, 1998) and U.K. (Sallybanks and Brown, 1999).

However, this study finds that there is a significant positive association between PC5, which reflects poverty, and MVT rates, but only during Periods One and Two (see Table 7-3). This finding for Periods One and Two is consistent with previous research in this area, which indicates that there is a positive correlation between poverty more generally and MVT in the U.S. (Flowers, 2006a; Copes, 1999; Hannon and DeFronzo, 1998; Messner and Blau, 1987). Based on Chapter 7, however, this study argues that these findings cannot be applied to all times of the day, as poverty showed no significance during Periods Three and Four. Furthermore, the OLS and ML regression results presented in Tables 7-3 and 7-6 show that neighbourhoods with a higher percentage of poverty tended to have a higher probability of MVT occurrences during Period One (midnight to 6 am) than in the other time periods. This could be explained by the RAT – i.e., MVT is more likely to occur in poor areas during sleeping hours where vehicles are parked outside houses instead of in secure car parks, reflecting an absence of capable guardians and a high presence of potential offenders living nearby.

Males aged between 15 and 24 is a second variable that was expected to have an effect on MVT. Results show that a younger population had a significantly negative effect on MVT during Periods Two and Four, while showing no significant effect on

MVT rates during Periods One and Three (Table 7-1). The negative effect of a young population on MVT rates during Periods Two and Three does not support the previous research in Canada (Andresen, 2006b), in the U.S. with temporary MVT rates (Roberts and Block, 2012) or in England and Wales (Sallybanks and Brown, 1999), which all showed a positive association. However, it seems to be consistent with the findings of Copes (1999), which found that an area with a young population – a southern U.S. parish – tended to experience low MVT rates. Meanwhile, the results from Period Three support the findings that there is no relationship with permanent MVT (Roberts and Block, 2012) in the U.S. and no significant effect on MVT in large metropolitan counties in the U.S. (Hannon and DeFronzo, 1998).

However, Table 7-3 reveals that PC4, which represents areas dominated by single people with a high percentage aged between 15 and 24, only had a significantly positive impact on MVT rates during Period One. The link with young males may explain why the percentage of single people showed the greatest positive effect during Period One, as single people who live alone were hypothesized as more vulnerable to being regarded as suitable targets when living in areas with a high percentage of young people. Consequently, the presence of a young population, who are more likely to be motivated offenders, and singles – "the suitable targets" – has led to an increase in the probability of MVT incidents occurring within these areas at the suitable time, which is when vehicles are parked near the homes of their owners during the hours of darkness. This can be supported by the ideas of Eck and Weisburd (1995), who suggest that criminals in their early years may tend to commit crimes near their own residence.

On the other hand, a possible explanation for the negative effect of a young male population on MVT rates during the daytime and evening is that MVT rates are based on vehicles that move from place to place. Hence, the risk occurs at places that attract a young population during the daytime due to the presence of different activities taking place within those areas. To clarify this, during the day, a large number of youths are likely to be at work, schools and recreational places. In addition, neighbourhoods with a high percentage of young people tend to have a lower percentage of vehicle owners (Copes, 1999), and we might therefore expect low rates in areas of young people more generally, only really reversing when local offenders are active. Thus, the results of this study showed that during the daytime and evening, areas with a high percentage of young people had lower rates of MVT. In addition, during sleeping hours – Period One – a young population showed a relatively positive effect only in areas highly dominated by single people, i.e. an effect was only shown when young single people were likely to have parked vehicles on the streets.

The findings of the current study contribute considerably in explaining the contradiction within previous studies in regard to identifying the effect of a young population. Previous studies examined the effect of young people on MVT for the whole day, overlooking the variations in the influence of predictors over space and time. Thus, the significance of this study is in detecting a more nuanced influence of young populations on MVT rates. It is found that the association between this factor and MVT rates varies from a positive effect during Period One in areas dominated by single people, to a significantly negative effect during working hours (Period Two) and evening time (Period Four), to no significant effect during the afternoon period (Period Three).

The percentage of non-Saudi males is used here to examine household activity away from the home, as the majority of non-Saudis are workers, representing more than 55% of the labour force (Central Department of Statistics and Information, 2008b), and it is expected that homes will be empty while they are working. The results presented in Chapter 7 show that non-Saudi males had a positive significant effect on MVT rates during the whole day, with the greatest effect during Period Four (Table 7-1). This could be taken to indicate offender concentrations, however, when this factor is included in PCA, it is highly correlated with PC1, which reflects areas predominately populated by foreign workers. Analysis of the current study reveals that PC1, representing foreign workers, significantly positively contributed to the prediction of MVT rates throughout the day, but the biggest effect was during working hours, whereas the lowest effect was during Period One – sleeping hours (Table 7-3). This is also confirmed by the results of the ML regression model, which show that areas with a high percentage of foreign workers are more likely to have MVT incidents during Period Two (6 am to 12 pm) in comparison to other periods (see Table 7-6). These results corroborate the ideas of RAT in that participation in the labour force increases the opportunity for property crimes to occur (Cohen and Felson, 1979). In general, non-Saudi males are correlated with property crime, backing up findings from Al-Khalifah (1997), who found that only a small percentage of foreign workers amongst the examined variables contributed significantly to positive predictions of property crimes in Riyadh. Al-Kharif (1998) found that the proportion of crimes committed by non-Saudis was higher than that committed by Saudis in SA. The results here show that this is at least in part because of the lack of capable guardians during the day, as much as the presence of potential offenders.

Despite the relationship between overseas workers and MVT, examination of the data suggests an intriguing contradiction: areas where a large proportion of foreign workers live tended to have a high proportion of people without vehicles (see Chapter 5, Table 5-10), which would seem to dictate a reduced relationship with MVT. Two things potentially mitigate this. Firstly, the results from the OLS regression model in Table 7-1 showed no significant contribution of the percentage of households with no vehicles (HNV) for predicting MVT rates. This suggests the relationship may not be influenced by the levels of no-car households. Secondly, and likely explaining this absence of a relationship between no-car households and MVT as well as the stronger relationship in areas of overseas workers, it is likely that cars move around far more than the census data can represent. Thus, the greatest impact on MVT rates for PC1, reflecting foreign workers, during working hours and the drop in influence during sleeping hours could be related to an increased availability of vehicles inside these areas during working hours. It may be that the high association between areas dominated by foreign workers with a high presence of households with no vehicles (HNV) and MVT rates is more clearly understood as a result of the increased density of vehicles during the daytime within these areas where there are potential offenders who have a lack of access to vehicles, along with the low levels of capable guardians.

These findings may help us to understand the contradictory results of previous studies. In the U.S., Copes (1999) did not find a significant effect for vehicle density, whereas Roberts and Block (2012) and Clarke, R.V. and Harris (1992) found a negative association between MVT rates and vehicle ownership. The findings of the present study highlight the fact that vehicles are not stationary objects. Thus, it is important to bear in mind the possible change in the density of vehicles within areas throughout the day, which has been overlooked by previous studies. Although this study has benefited from taking into account the change in MVT occurrences throughout the day, by examining the density of different road types, the current findings suggest that it would be interesting for future research to investigate the effect of traffic volume and static traffic locations on MVT occurrences.

8.2.2 Suitable Targets

As indicated earlier, findings reveal that areas dominated by single people and with a high presence of young people (reflected in PC4) tended to show a significant positive effect on MVT rates only during Period One (Table 7-3). These results support the theme within RAT that suggests single adults living alone are suitable targets for property crime offenders (Cohen and Felson, 1979), in particular during sleeping hours. This could be due to vehicles being parked outside houses rather than in expensive secure storage, as well as a lack of capable guardians.

It was expected that neighbourhoods with a high proportion of rented houses would tend to experience higher MVT rates due to vehicles being parked on the streets, but contrary to expectations, the findings reveal no significant impact (as shown in Tables 7-1 and 7-2). However, the study shows that poor areas (PC5) with a high percentage of households who are renters had a significant positive association with MVT rates during Period One – sleeping hours (Tables 7-3, 7-6). Overall, this finding slightly corroborates the findings published by previous studies in England and Wales (Clarke, R.V. and Mayhew, 1994; Sallybanks and Brown, 1999) and in the U.S. (Flowers, 2006b; Harlow, 1988; Weisel et al., 2006), which indicated a higher level of MVT in places with higher percentages of rented houses. However, the findings of previous studies need to specify the times of day regarding the effect of rented houses and the types of areas in which they are located. The findings of the present study suggest that the significantly positive effect of rental housing in Riyadh is in poor areas during Period One – midnight to 6 am – while this factor showed no significant effect on MVT rates during all times when standing alone, as can be seen from the results in Chapter 7. In Riyadh, it is less likely that the poor engage with the kind of expensive private secure garages seen in wealthy areas.

The density of roads was examined in relation to how it affects the availability of suitable targets based on the finding of Copes (1999), and it was also tested to reflect the CPT themes suggesting that crime is more likely to occur near activity nodes along specific paths (road networks) (Brantingham, P.L. et al., 2011; 2008; 1993). However, as found in this study, road density is more related to CPT themes than RAT. A discussion of the examination of road density will be presented in Section 8.3 under CPT.

8.2.3 Absence of Capable Guardians

It was hypothesized that male population density may play a role in guardianship based on a suggestion of RAT that passers-by could act as capable guardians to prevent crime (Felson, 1986). Contrary to expectations, this study found that PC2, which reflects the density of roads and the male population, had a significant positive effect on predicting MVT rates during Period Four but no significant effect on MVT rates during Periods One, Two and Three (Table 7.3). These results from OLS are in line with the results from the ML model showing that neighbourhoods with a high density of PC2 are more likely to have higher MVT incidents during Period Four than in the rest of the day (Table 7-6). Meanwhile, the finding from the OLS regression models for MVT rates using the integrated theory models suggest that a high density of population with a high density of facilities – “PC2” – significantly positively contribute to predicting MVT rates during Periods Two, Three and Four but have no significant effect in Period One (Table 7-13). Moreover, it is important to note that the results from the ML regression model in Table 7-18 indicate that the mixed land use – high population density and high density of facilities – tended to have higher MVT incidents during Period Four than in other periods.

In general, the results are somewhat in agreement with those obtained by Copes (1999), who found a positive relationship for population density in the US. This is in contrast to the findings of Rice and Smith (2002), who reported a negative relationship in the US, and the findings of Andresen (2006b) and Kennedy and Forde (1990), who found no significant influence on MVT rates in Canada. However, the findings of the present study have important implications in that the density of population varies in its influence according to the time period. The population density is most significantly positive during the evening time from 6 pm to midnight (Period Four) in areas with a high density of facilities, such as shops and restaurants.

Andresen (2006b) and Copes (1999) used population density to represent capable guardians in order to explain MVT under RAT. However, both studies found that population density runs contrary to their expectations. In that respect, the findings of the current study do not support the idea that population density represents an increase of capable guardians, because it positively affects MVT rates. Furthermore, a high density of population does not necessarily mean that there are more vehicles available. There are, however, other possible explanations for this: there may be higher traffic volume within these neighbourhoods due to the presence of facilities that attract people to these sites. The obvious evidence supporting this argument is that population density does not have a consistent significantly positive effect on MVT rates over the whole day. It has no impact on MVT rates during Period One – sleeping hours (12 am to 6 am) – when the population density is still present but the facilities are closed. While during the evening, the population density plays an important role at certain times, i.e. when there is high density of open facilities. These findings seem to be consistent with the argument discussed earlier in Chapter 4 that MVT in SA is expected to be limited in residential areas where facilities are distributed along the streets. Public Security (2016) and Al Angari (2002) showed that leaving vehicles unattended while the engine is running is the main behaviour associated with vehicle theft in SA.

Ethnic diversity is generally used to assess the amount of capable guardians (see Section 5.3). A highly diverse community is said to lead to lower social cohesion (Laurence and Bentley, 2016) and a consequently high crime rate (Hirschfield and Bowers, 1997). Hipp (2007) suggested that people who live in a cohesive community might act as capable guardians and consequently reduce the opportunities for crime. Contrary to expectations, this study shows that diversity significantly negatively correlated with MVT rates during every period (Table 7-2) and significantly negatively predicted MVT rates during Period Two (6 am to noon) (Table 7-1). These results are in line with the findings of Andresen (2006b), who found that levels of ethnic heterogeneity have significantly negative relationships with MVT rates in Vancouver, Canada, while they are in contrast to the findings of Walsh and Taylor (2007b) in the U.S. and Sallybanks and Brown (1999) in England and Wales, who found a positive relationship, and Rice and Smith (2002), who did not find a significant relationship in the southeastern US. These previous contradictory results may be due to the different methods used in each study for measuring racial/ethnic heterogeneity within the studied areas, or they may highlight the nuanced relationship between diversity, cohesion, and crime. Here, the negative effect of diversity could be related to these areas in Riyadh tending to have wealthier social conditions (and thus more secure garages). As can be seen from Figure 5-3E, these northern areas with high diversity are negatively correlated with poverty: PC5. It is not a given that diversity is linked with low community cohesion in all societies or for all communities.

It was hypothesized that areas with high numbers of employed females might tend to have high MVT rates due to the lack of capable guardians in these households. This hypothesis was formulated based on the themes of RAT, which suggest that married females who are employed positively influence property crimes due to the absence of capable guardians from homes during working hours (Cohen and Felson, 1979). Contrary to expectations, the results of this study show that the percentage of employed females had a significantly negative impact on MVT rates during all times (Table 7-1). Furthermore, the analysis shows that areas with a high percentage of employed females tend to be more diverse (Saudis and non-Saudis) and more residential, as reflected in PC3 in Table 7-3. The areas with PC3 tended to have lower MVT rates. This result is in contrast to the findings of Hannon and DeFronzo (1998), who found a positive effect of the participation of females in the labour force on MVT in the U.S. (large counties). In SA, participation in the workforce indicates that families have good economic conditions, and vehicles within these areas are more likely to have good security systems and be parked in secure car parks (see Figures 5-3 C and E).

It was expected that housewives would act as capable guardians based on the themes of RAT (Felson, 1986), as staying at home during much of the day would protect vehicles parked near houses. However, the findings of this study suggest that there is no significant contribution of the percentage of housewives variable in predicting MVT rates during all times. Although a correlation matrix (Table 7-2) showed a (weak) significant positive correlation between the percentage of housewives and MVT rates during Periods Two, Three and Four, it has no significant contribution in predicting MVT (Table 7-13, 7-18). The combination of these findings yielded from the empirical work of this study confirms the issue highlighted in Chapter 4, Section 4.3, whereby the occupants of houses in SA are unable to protect vehicles parked on the street due to the surrounding high walls (also see Figure 3-8). These findings raise important questions regarding the applicability of theories to different contexts (see Section 8.2.4).

Nevertheless, the combination of findings here clearly suggests that vehicles parked outside homes are more vulnerable to vehicle theft during sleeping hours than in other periods of the day, whereas MVT tends to occur during the evening between 6 pm and midnight in residential areas characterized by a high density of population and facilities. This is in contrast to the West, where MVT tends to occur on the street outside the victim's home (McCormick et al., 2007; Weisel et al., 2006; U.S. Department of Justice, 2000; Clarke, R.V. and Mayhew, 1994; Fleming et al., 1994). Henry and Bryan (2000) examined spatial-temporal patterns in Adelaide and found that the highest frequency of motor vehicle theft occurred late at night, from 1 am to 3 am.

Overall, the negative influence of employed females and no significant effect for the percentage of housewives in predicting MVT rates run contrary to those conditions proposed by RAT, which have successfully explained burglaries in the West.

Another factor used to measure levels of guardianship is the average family size. It was hypothesized that if the average family size increases in neighbourhoods, MVT rates will decrease as a result of the presence of more guardians. However, the picture is more complicated, as we have found that areas dominated by foreign workers presented in PC1 tended to have higher percentages of small family size and higher MVT rates during all times (Table 7-3). Meanwhile, the results showed that PC5, which reflects poverty and correlated with large family size, had a significant positive impact on MVT rates during Periods One and Two (Table 7-3). This discrepancy could be attributed to the average family size not being significant in representing capable guardians, but instead representing deprivation.

From the previous discussion, it is apparent that the absence of capable guardians is difficult to determine for MVT, since the proposed variables provide the opposite effect to those hypothesized. This has also been reported for other MVT studies, such as Roberts and Block (2012), Andresen (2006b) and Copes (1999), who found no association between variables used to measure capable guardians and MVT occurrences. This should be contrasted with burglary, where this element can be clearly measured by houses' occupants, whether by the absence of employed females or the presence of housewives. For example, burglaries are more likely to occur during working hours when people's houses are empty, meaning an absence of capable guardians (Cohen and Felson, 1979).

8.2.4 Evaluating the Applicability of RAT

This study has been unable to demonstrate that the variables used to represent RAT's elements proposed by Cohen and Felson (1979) consistently contribute to increased MVT rates throughout the day. The study found that some explanatory factors showed their greatest effects on MVT at specific time periods, with no significant prediction for MVT at other time periods. This result could be due to two critical factors. First, the conditions in the West, where this theory originated, differ from those of the Saudi Arabian context. Second, the nature of MVT is different from that of burglaries and robberies, which are the crimes to which RAT has most frequently been applied.

Importantly, the treatment of the variables associated with RAT here suggests that its underlying explanatory factors vary throughout the day, which is rarely accounted for in crime studies. The socioeconomic and demographic characteristics of neighbourhoods that represent motivated offenders make the greatest contributions to predicting MVT during Period One (midnight to 6 am) – sleeping hours. Meanwhile, routine household activities display significant predictive power for MVT rates during Period Two (6 am to noon) – working hours. However, the findings of the present study provide no support for the influence of the variables used to measure the absence of capable guardians: male population density, diversity, percentage of employed females, family size and percentage of housewives. This result might be explained by the fact that these variables are related to burglaries, not MVT, which is somewhat different in nature.

This lack of applicability for some variables used to explain MVT under RAT can be seen when using variables to represent the absence of capable guardians. A lack of capable guardians can be applied to burglary, as people leave their houses during working hours (Cohen and Felson, 1979), but in the case of MVT, people take their vehicles with them, in particular in SA as vehicles are the main form of transportation. Copes (1999) also highlighted this limitation of representing guardianship using houses' occupants. Furthermore, the difficulty of representing this element of MVT can be seen in previous studies. For example, published studies on the effect of population density are not consistent. Andresen (2006b) and Copes (1999) both used population density to represent guardianship, but the former found no significant effect, while the latter found a positive effect, contrary to their expectations. Roberts and Block (2012) also used multiunit housing to measure the effect of capable guardians and did not find a relationship with MVT rates. The combination of these findings raises questions regarding the relevance of socioeconomic and demographic variables in reflecting levels of capable guardians for MVT.

To our knowledge, this is the first study to examine statistically the temporal variations in the influence of variables on MVT occurrences. Previous MVT studies have treated the contributing factors as having a consistent influence on MVT throughout the day, which has led to ambiguous findings. In contrast, this study found that the impacts of some examined factors on MVT rates change from positive to negative and to having no significance throughout the day. Thus, the generalizability of published research suggesting a factor's consistent influence on a type of crime throughout the day is not realistic. Good illustrations of these variations in the effects of explanatory factors are as follows:

- Poverty was the most significant predictor during sleeping hours but showed no significant effect on MVT rates during the evening.

- The percentage of foreign workers showed the greatest significant contribution to predicting MVT rates during working hours.

- Population density (PC2) showed a significant effect on MVT rates during Period Four (6 pm to 12 am) but no significance during other periods.

- Vehicles parked near the homes of victims are more likely to be targeted during sleeping hours than during other periods of day.

Overall, we should be more precise and cautious when using the term ‘property crimes’ in analysis and when applying theories, as each crime differs considerably in its nature, conditions and contributing factors. MVT is different from other property crimes, such as burglary, which has been the main topic explored through the application of RAT. In MVT, the suitable target is not a stationary object, whereas in burglary, the targets are houses. Thus, burglary can be better explained and interpreted under an environmental approach to RAT, whereas the conditions of MVT depend heavily on the activities of people, who move from place to place throughout day. This makes the picture more complicated for explaining patterns of MVT by socioeconomic and demographic variables during the afternoon and evening periods, when vehicles are more likely to move. This is evident from the OLS regression models not performing well in explaining MVT rates during Periods Three and Four (Table 7-5). Meanwhile, when vehicles tend to be stationary (parked) during Period One (sleeping hours) and Period Two (working hours), the results from the OLS regression models performed well in explaining MVT (see results from the OLS regression models in Table 7-3 and global Moran’s I in Table 7-5).

Furthermore, the findings examining the models indicate that RAT works best during Period Two (6 am to 12 pm) – working hours. The regression models for Period Two consistently appear to be better models compared to the other periods (see Table 7-3). In contrast, despite Period Four having the largest proportion of MVT incidents of all the periods, the results indicated that the regression model for MVT during this period exhibited a less satisfactory explanation for MVT rates than during Period Two. This suggests that Period Four is very different from Period Two and the other periods. It is therefore likely that a key variable (or variables) not examined might contribute significantly to MVT during Period Four. These results further support the idea that RAT, or at least factors formulated to reflect RAT themes, is mainly based on the role of working-hours patterns. Cohen and Felson (1979) argued that burglaries have increased with the proportion of married women entering the workforce and the number of people travelling to work in general. Thus, crime patterns might vary based on working hours, which this theory explained well, as burglary occurs most often during daytime hours (Filbert, 2008; Grabosky, 1995; Hakim and Gaffney, 1995). However, MVT is different from burglary and tends to be most frequent during the night, as reported in a wide range of studies (Flowers, 2006b; Weisel et al., 2006; Clarke, R.V., 2002; Henry and Bryan, 2000; Mirrlees-Black et al., 1996; Fleming et al., 1994), including the present study. This is an important implication for future research, which should concentrate more on the evening and night periods when MVTs are more likely to occur, at least in the West, where car risk and census variables may match better.

An evaluation of RAT reveals that MVT has been given little consideration. So far, the MVT studies reviewed have produced weak models when applying RAT. For example, in a study by Andresen (2006b) investigating crimes, the regression model for MVT provided the lowest level of explanation (55% of variation) compared to burglaries (64%) and violent crimes (77%). Other studies, such as Rice and Smith (2002), explained only 25%. These poor levels of explanatory power could be due to the lack of understanding of factors that influence MVT and treating MVT in the same way as other types of property crimes. This study found that the explanatory variables associated with RAT varied in their powers of explaining MVT rates throughout the day – from explaining 42% of MVT variations during Period Three to explaining nearly 60% of MVT variations during Period Two (Table 7-1).

In general, the variables that were chosen to explain MVT under RAT work better when vehicles are stationary, but when vehicles move from place to place, the variables show less interpretive power. This is especially true in SA, where cars *en route* are more at risk, but applications of RAT also offer few insights into the causation of MVT in the West. Therefore, more work is needed to capture a full picture of MVT occurrence utilising RAT.

8.3 MVT and CPT

The goal of this study was also to use crime pattern theory (CPT) to explain MVT in Riyadh. The main themes of CPT, as discussed previously in Chapter 2, involve crime generators, crime attractors, activity nodes and paths (Brantingham, P.L. et al., 2011; 2008; 1993). Therefore, this section is divided into aspects based on these themes.

8.3.1 MVT Generators

Residential areas are neighbourhoods allocated specifically to residential use. The study reveals that neighbourhoods classified exclusively for residential use tend to have lower MVT rates. The regression models for CPT clearly show that PC2, which represents residential areas, had a significant negative effect on MVT rates throughout the day (Table 7-9). This result matches observations by Al Angari (2002) based largely on a sampling of car thieves in Saudi prisons, suggesting that vehicles stolen while left unattended on the street with the engine running accounted for a greater proportion than those vehicles stolen while parked outside victims' houses. However, the finding of the study here does not support the previous research of Western studies on MVT. These studies reported that the majority of cars were stolen from driveways near owners' houses in Canada (McCormick et al., 2007; Fleming et al., 1994), Sweden (Ceccato et al., 2002), the U.S. (Weisel et al., 2006; U.S. Department of Justice, 2000) and the U.K. (Clarke, R.V. and Mayhew, 1994).

This discrepancy between the patterns of MVT in SA and the West could be attributed to differences in the built environments. The concept of CPT enhances the perceived role of the built environment in influencing potential offenders' decisions to commit crime (Brantingham, P.L. et al., 2011; 2008; 1993). The effects of different built-up environments on the applicability of theories are discussed in Chapter 4, Section 4.3. The obvious factor that might affect the crime template is that the main method of transporation in SA is by car due to the lack of other transport systems, such as buses and trains, inside Riyadh (as discussed in Chapter 3). Thus, during working hours, there are fewer targets near homes in SA compared with Western countries. For example, due to the avaibility of public transporation systems (buses, trains, etc.) in the West, many people leave their vehicles parked next to their homes during working hours. This is due to reasons such as the lack of available parking spots at the workplace. For example, in the UK, people travel to work using buses more frequently than any other method of transport (Mackie et al., 2012). Hope (1987) pointed out that, according to the British Crime Survey, residents who leave their vehicles for longer periods because they commute to work by walking or taking other forms of transport are at greater risk of becoming victims of MVT. The results of the CPT model shown in Table 7-9 are in line with this observation, as they show that residential areas are less attractive for potential offenders during Period Two (6 am to 12 pm) – working hours in Riyadh, SA.

A second factor that can reduce the likelihood of MVT occurring in residential neighbourhoods during the daytime is a lack of established footpaths within these areas in SA, and thus walking is not common within neighbourhoods (see Figure 3-7 in Chapter 3). Thus, occurrence of MVT in residential areas tends to be limited to sleeping hours when vehicles are parked outside the houses of victims. This finding is supported by the findings revealed in Section 8.2, suggesting that residential areas are more likely to experience higher MVTs during Period One than in daytime (see results of ML regression models in Tables 7-6, 7-12, 7-18).

Analysis of the regression models indicates that areas classified as residential with a high density of facilities and roads (presented in PC1) tend to have higher MVT rates throughout the day (Table 7-9). This type of land use tends to have the highest positive contribution to predicting MVT rates during the evening (Period Four – 6 pm to midnight) and the lowest effect during the night (Period One – midnight to 6 am). Therefore, we could say that in Riyadh, SA, as the built-up environment and demographics are apparently different from the West, vehicles tend to be stolen in areas that are of mixed use and have both residences and facilities, such as restaurants, shops and offices services. The results of CPT are in agreement with those obtained by RAT in Section 8.2, showing that neighbourhoods with a high density of population and facilities tend to experience higher MVT rates during Period Four. The integration of the theories showed that the variables of population density and facilities highly correlated with PC2 (Table 5-12). The results of regression models for MVT rates utilising the integrated theories also indicate that PC2 had a positive significant impact on MVT rates during Periods Two and Three, with the greatest effect during Period Four. One study, by Henry and Bryan (2000) in Australia, which observed areas with various facilities such as restaurants and bars, illustrated that these are hotspots for MVT incidents. However, our findings highlight here the influence of those facilities when they are located specifically in areas with a high population density in Riyadh.

Moreover, the findings here indicate that the percentage of apartment buildings has a significant positive effect on MVT rates during all periods (Table 7-7). These findings concur with other studies that suggest a higher likelihood of MVT for people who live in terraced houses or flats in England and Wales (Clarke, R.V. and Mayhew, 1994), and flats in Sweden (Ceccato et al., 2002). Furthermore, the result of the PCA indicates that the percentage of apartment buildings tended to be higher in mixed-use land areas (PC2 – high population density and facilities) (see Table 5-12).

One interesting finding is that commercial areas show a weak negative correlation for Periods One and Two (midnight to noon), whereas they exhibit a weak positive correlation with Periods Three and Four (noon to midnight) (Table 7-8). These correlations are not significant, however. This can be seen as the regression models reveal that commercial land use had no significant contribution to predicting MVT rates during the day (see Table 7-7). PC6, which reflects commercial areas, had no significance in predicting MVT, as shown by the results from the OLS regression model (Table 7-13) and ML regression models (Table 7-18). Previous research by Kinney et al. (2008), based on observation, found that commercial areas tended to show hotspots for MVT during working hours, which differs from the findings presented here. A possible explanation is that vehicles in these commercial sites are more likely to be parked in secure car parks in Riyadh. Thus, there are few MVT opportunities, and car thieves in SA tend to target vehicles that are left unattended with the engine running (Public Security, 2016; Al Angari, 2002).

One of the clearest findings to emerge from the analysis is that PC7, which reflects recreational areas, showed only a weak significant positive contribution to predicting MVT rates during Period Four (6 pm to 12 am) (see Table 7-13). Furthermore, the results of both the OLS regression models in Table 7-9 and the ML regression model in Table 7-12 reveal that areas with a high proportion of recreational use with some presence of commercial use (as can be seen in PC4) indicate a significant positive effect on MVT rates during Periods Three and Four (noon to midnight). The finding of the positive effect of recreational places on MVT rates matches the observations by Henry and Bryan (2000), who highlighted that the hotspots for MVT incidents appeared in the business and recreational sites across Adelaide, Australia. Furthermore, these results confirm the positive association between areas that are classified as mixed-use for recreational and commercial purposes and MVT incidents, which was indicated by Kinney et al. (2008). Moreover, these findings support the CPT concept that activities attract more vehicles (with potential offenders and suitable victims) at certain times (Brantingham, P.L. et al., 2011; 2008; 1993) which in this case is the evening (Period Four, 6 pm to midnight).

A further important type of land use is industrial. The findings of the regression analysis indicate that industrial areas significantly contributed to predicting MVT rates during Periods Two, Three and Four. This is in agreement with the findings of Weisel et al. (2006) and the study by Saville and Murdie (1988) that showed residential and industrial areas having high incidences of MVT.

8.3.2 MVT Attractors

The study shows that car parks had a significant positive contribution to predicting MVT rates throughout the whole day, and the highest probabilities of MVT occurrences are during Periods Two and Three (6 am to 6 pm). This finding corroborates the element of CPT as hypothesized, which suggests that car parks work as crime attractors for potential offenders. Furthermore, this result seems to be consistent with other research that found car parks accounting for a high frequency of MVT incidents in the U.S. (U.S. Department of Justice, 2000; Rengert, 1997), Australia (Drugs and Crime Prevention Committee, 2002; Higgins, K., 1997), England and Wales (Sallybanks and Brown, 1999) and Canada (Wallace, 2003; Fleming et al., 1994).

Another finding of this study is that car facilities, which include any site provides car services, such as car repair shops and shops that sell cars, showed a significant positive contribution to predicting MVT rates throughout the day. Moreover, the greatest contribution to predicting the probability of MVT occurrences happened during the daytime – Periods Two and Three (6 am to 6 pm). This finding matches those observed in earlier studies showing that car facilities are more vulnerable to high concentrations of MVT in the U.S. (Roberts and Block, 2012; Weisel et al., 2006). However, this finding differs from the recent Canadian statistics (2007) on MVT that showed car dealerships and car rental agencies had a very low percentage of MVT incidents, accounting for only 1% of all MVT in Canada (Dauvergne, 2008). Therefore, a possible explanation for this might be that car facilities in Riyadh, SA, are more attractive for potential offenders, and this could be due to the lack of security systems during the workday.

8.3.3 Paths and Nodes

The densities for five types of roads were examined in this study under RAT to measure the availability of suitable targets and under CPT to reflect paths and activity nodes. It was hypothesized that areas having a high density of roads will have a high availability of vehicles and thus high MVT rates. The hypothesis is based on the finding of Copes (1999), which suggested a positive relationship between the density of roads in neighbourhoods and the rates of MVT. However, there is a potential for bias in examining this hypothesis using all types of roads. Copes (1999) finding differs from the findings presented here, which here suggest that not all densities of road types have the same significance in influencing MVT rates. The findings of this study suggest that certain types of roads exhibit a significantly positive effect on MVT rates during certain periods of time, while others show a negative effect. Here, we find that freeways "A" presented in PC6 had a negative effect on MVT rates during Period Two (Table 7-3), while PC 2, which reflects the collectors "D" and residential areas, had a significantly negative effect on MVT rates during all periods (Table 7-9). In contrast, high densities of arterials "C" present significantly positive contributions to predicting MVT rates only during Period Four (Table 7-7).

Another important finding was that major roads "B" were only statistically significant with regard to having a negative impact on MVT rates during Period One (12 am to 6 am) (see Table 7-7), whereas areas with a high density of this type of road tended to show a significantly positive effect on MVT rates during the other periods. Although these results are in agreement with some published studies (Suresh and Tewksbury, 2013; Lu, 2006), revealing that major roads tend to have a higher frequency of MVT incidents, they are inconsistent with them during Period One – sleeping hours. Thus, caution must be applied, since the positive effect of major roads density on MVT rates cannot be generalized without taking into account the results of examining the spatial and temporal variations.

The current study reveals that areas with a high density of roads classified as major ('B'), arterial ('C') and local ('E'), as reflected in PC2, are more likely to have MVT incidents during Period Four – evening time – than during the other periods (Table 7-3 and Table 7-6). The observed increase in MVT incidents during Period Four could be attributed to the routine activity of people in these areas, i.e. doing activities or shopping within these areas during the evening time, which is common in SA because of the climate (see Figure 3-4 showing traffic volume trends in Riyadh).

However, the negative effect for freeways could be attributed to these roads tending to have few facilities and few activities taking place along them in comparison to other types of roads. In addition, these types of roads have few entrances and exits, and thus they are not attractive locations for potential offenders. Therefore, this finding is in disagreement with the findings of Matthews et al. (2010), in that freeways have a positive association with MVT in Seattle in the U.S. On the other hand, arterials “C” showed the most positive effect of MVT occurrence in comparison with other types of roads (see Table 7-2 and Table 7-7), which is probably due to the highest presence of facilities on this type of road, as they attract many people for activities, such as shopping, throughout the night (6 pm to midnight) (as indicated in Chapter 5). This finding seems to be consistent with other studies, which found certain activities taking place along roads (Lu, 2006).

Both arterials “C” and freeways “A” exhibit high traffic volumes during different times, but the main difference between them is their density of facilities, not the density of vehicles (see Section 5.3 in Chapter 5). Therefore, the combination of findings provides stronger support for the CPT theme of the influence of nodes of activities and paths rather than the elements in RAT for the concentration of suitable targets. The finding supports the claim in earlier research by Rengert (1997) that RAT has overlooked the influence of attractive locations that bring potential offenders and suitable targets together at certain times, which has been emphasized by CPT. Furthermore, it has been suggested that an increase in traffic volume results in an increase in potential targets (victims, vehicles) (Rice and Smith, 2002; Beavon et al., 1994); however, this finding is somewhat inaccurate. The present study found that freeways have high traffic density at certain times but clearly have a negative impact on MVT rates. The key factor giving traffic density a positive effect is the presence of facilities that can be easily accessed from the road. A potential drawback to the analysis conducted here is that traffic density will vary within road types, but we assume that all roads of a particular type will exhibit similar volumes of traffic. Nevertheless, these findings raise interesting questions regarding the effect of traffic volume on the spatial and temporal distribution of MVT, which could be investigated in depth in future research.

8.3.4 Evaluating the Applicability of CPT

The result of regression models showed that the factors representing CPT themes provided poor explanatory power for MVT rate variations during Period One (12 am to 6 am), whereas it exhibits a better explanatory power for MVT rates during Period Two (6 am to 12 pm) (Tables 7-7, 7-9). The reason could be that during sleeping hours (Period One) vehicles are parked near the homes of car owners. Thus, the socioeconomic and demographic variables are more relevant in explaining MVT rates during Period One (12 am to 6 am) than the environmental features. This can be seen in the effect of these variables (socioeconomic and demographic) when examining RAT (Section 8.2). On the other hand, despite the occurrences of MVT during Period Four (6 pm to midnight), which accounted for the highest frequency, the theory had less explanatory power for the variation of MVT rates during this period when compared with Period Two, which seems to be consistent with the results of examining RAT (Section 8.2). However, the results from diagnosing the spatial autocorrelation of residuals showed that none of the OLS regression models for MVT under CPT performed well in explaining MVT throughout the day (Table 7-11). This suggests that environmental features representing CPT were not sufficient to explain MVT, and it was essential to include socioeconomic and demographic factors in order to improve the explanatory power of regression models.

With regard to how well environmental features predict MVT throughout the day, the current finding supports CPT's concept that activity nodes attract potential offenders and suitable targets at certain periods of the day (Brantingham, P.L. et al., 2011; 2008; 1993). The results of examining factors representing CPT themes clearly showed fluctuations in their effects on MVT occurrences. A good example of the variation of the influence of built environments over time is the effect of recreational and commercial areas. These features showed negative correlations with MVT rates during Periods One and Two (midnight to noon), whereas their effects change to show a positive correlation with MVT rates during Periods Three and Four (noon to midnight) (Table 7-8). A possible explanation could be that during the morning hours there are few or no activities within these areas. Consequently, few or no vehicles are parked on the associated streets during these times, whereas it is the opposite situation in the evening. Furthermore, industrial areas indicated a significant positive effect in predicting MVT rates during Periods Two, Three and Four (6 am to midnight), whereas they showed no significant effect during Period One (midnight to 6 am). As a further example, the density of major roads “B” showed a significant negative effect on MVT rates during Period One but contributed positively to predicting MVT rates during the other periods. Overall, this study suggests that the characteristics of built environments show greater changes in their effects (from positive to negative) on MVT rates throughout the day than socioeconomic and demographic variables. However, they exhibit a lower power of explanation for MVT throughout the day, particularly during Period One – sleeping hours – and Period Two – working hours.

8.4 Integrating RAT and CPT

The results of integration between RAT variables and CPT variables were presented in Chapter 7, Section 7.4. To our knowledge, no studies have integrated variables representing RAT and CPT to model MVT. Here, eight components representing the themes of both theories were derived by utilising PCA (see Chapter 5 in Table 5-12). These PCs provided sufficient descriptions for the characteristics of Riyadh, that is, this integration improved the explanatory power of the regression models in explaining MVT variations. For example, the OLS regression model for MVT rates during Period Two explained 56% of MVT variation under RAT and 48% under CPT, but this explanatory power reached 64% of MVT variation when utilising the integrated theories. Overall, as with previous OLS regression models for RAT and CPT, both models for the integration of the theories for MVT rates during Periods One and Two showed that the residuals were more independent from each other than in Periods Three and Four (seen from the Durbin–Watson statistics in Table 7-13). As discussed in Section 8.2.4, this can be explained by the fact that during these periods of sleeping hours and working hours, vehicles are more likely to be stationary, so the explanatory variables work better in capturing the variations of MVTs, whereas during the afternoon and evening, vehicles are more likely to move from place to place. In regard to predictors for the integrated theories, their effects have been discussed in Sections 8.2 and 8.3 in order to relate the discussion to themes of each theory.

Interestingly, even with the integration of both theories, the regression model for MVT rates during Period Four did not perform well in explaining MVT (see Table 7-15). Therefore, GWR was conducted to improve model performance and also identify the local variations in the relationships between MVT rates and the predictors. The results of GWR showed that all GWR models performed well in explaining MVT in terms of spatial variables, as the spatial autocorrelations for the residuals were random (see Table 7-17). One significant contribution of this study is in detecting the variations in performance for models and coefficients across the study area and throughout the day. The results from GWR reveal important findings with regard to the levels of performance for regression models for MVT rates throughout the day and across the study area.

Although the results of regression models indicate that MVT rates during each period are affected by certain factors, Period Four showed greater critical difference from other periods. The finding highlighted in Chapter 6, which was based on the result of conducting the spatial point pattern test, is in line with those findings yielded from regression analysis, in that MVT rates during Period Four are very different. This finding is also evident from mapping the explanatory power for GWR models. The local regression models for MVT rates during Period Four exhibited the worst performance in the eastern neighbourhoods, whereas this was the case during Periods One, Two and Three in the north (see Figure 7-2). A further example of the difference between Period Four and the other periods was that PC1 (foreign workers) had the strongest positive effect on MVT rates during Periods One, Two and Three in neighbourhoods located in the south of Riyadh, as well as some parts of the central districts, but it had the strongest positive effect during Period Four in the northern and southern neighbourhoods (Figure 7-3D). This is in line with the result of mapping the OLS residuals during Period Four, which shows that the large positive residuals were clustered in the eastern areas of Riyadh, suggesting under-predictions, as shown in Figure 7-1. Therefore, it would be useful if future work investigated these under-predictions in eastern areas, as there would be a variable (or variables) that could provide greater interpretative power for MVT rates within these areas than actual variables. Overall, the results from GWR are useful for policymakers in identifying which neighbourhoods have a high demand for tackling MVT. Reflections on current police practice are in the following chapter.

8.5 Summary of the Chapter

This chapter has discussed the results obtained from the analysis chapters, concentrating on Chapter 7, in order to understand MVT in Riyadh under RAT and CPT. To achieve this goal, Chapter 8 began by discussing the results yielded from modelling MVT utilising the core themes of RAT in Chapter 7. The findings suggest that examining the effect of factors on MVT throughout the day is a very important aspect in understanding MVT, as each factor varies in the degree of its effect on MVT from one period to another throughout the day. The findings of utilising RAT elements indicate that socioeconomic and demographic variables used to measure motivated offenders tend to predict MVT during Period One (sleeping hours) and Period Two (working hours) when vehicles tend to be parked outside houses (see Section 8.2). However, during Periods Three and Four, when vehicles are more likely to be moved, the variables that were used specifically to measure motivated offenders did not predict MVT. Furthermore, the findings of examining RAT elements revealed that variables used to represent household activity and suitable targets, such as foreign workers, showed the greatest contribution to predict MVT during Period Two – working hours.

Five factors – percentage of employed females, percentage of housewives, population density, average family size and diversity index – were used to measure the absence of capable guardians in Section 8.2.3. Surprisingly, none were found to act as capable guardians. This was in agreement with other studies that were unable to measure capable guardians (Andresen, 2006b; Copes, 1999) but against the general themes of the RAT literature. Thus, it can therefore be argued that the absence of capable guardians is difficult to determine for MVT in SA using socioeconomic and demographic variables (Section 8.2.3). Having discussed the factors used to predict MVT under RAT themes, Section 8.2.4 evaluated the applicability of RAT. Overall, explanatory factors used to represent the elements of RAT performed well in explaining MVT variations when vehicles tend to be stationary, whereas they performed unsatisfactorily when vehicles are more likely to move from one site to another. This could be attributed to the fact that the Western context, where RAT was developed and proposed, is very different from SA. In addition, RAT has been largely applied to explain burglaries, whereas little research has studied MVT under RAT.

With regards to the themes of CPT discussed in Section 8.3, due to substantial differences between the contexts of SA and the West (see Chapter 3), several findings presented in this study contrast to those found in Western studies. The findings of this study indicate that, in line with the West, during sleeping hours MVT is more likely to occur near victims' homes than at other periods of the day. However, this period accounted for the lowest proportion of MVT, which is a contrast to the West, as the majority of MVTs occur on driveways near owners' houses at night (McCormick et al., 2007; Weisel et al., 2006; Mirrlees-Black et al., 1996; Clarke, R.V. and Mayhew, 1994; Fleming et al., 1994). Furthermore, a key finding emerged from this discussion showing that areas with a high population density and facilities, such as shops, contributed significantly to predicting MVT during the evening. This is an interesting finding, as within these areas some people in SA tend to leave their vehicles unattended with the engine running while they are paying for goods, which is in line with Saudi studies on the opportunities exploited during MVT (Public Security, 2016; Al Angari, 2002).

The discussion in Section 8.3 revealed that each road type varied considerably in its influence on MVT occurrences throughout the day, suggesting that the ambient traffic volume and presence of facilities along them plays an important role in their effects. This is a vital finding that was overlooked by the reviewed studies (Suresh and Tewksbury, 2013; Lu, 2006; Copes, 1999). The evaluation of CPT in Section 8.3.4 indicated that some environmental features exert different effects, fluctuating from positive to negative throughout the day. Certain features attract people, and consequently crime, at various times during the day, whereas at other times, these areas have no activities taking place and thus no motivated offenders or suitable targets attracted to them. Thus, findings suggest that studied factors under CPT did not perform well in explaining MVT rates throughout the day, and it is likely that the poor performance could be a result of missing socioeconomic and demographic variables (see Section 8.3).

In Section 8.4, modelling MVT under the integration of theories was discussed. The discussion revealed how the OLS regression models improved in performance when the variables associated with both theories were combined. One of the most important findings of the present study is that both theories mainly followed the working-hours patterns for burglaries. Therefore, modelling MVT during Period Two utilising RAT, CPT and the integration of the theories consistently had the best explanation for MVT rates of any time period. In contrast, modelling for MVT rates during Period Four (6 pm to midnight) under these theories and their integration suggests that MVT during Period Four requires further investigation to provide a better explanation. Therefore, GWR was used and revealed critical findings in terms of identifying local variations and assessing model performance. The findings suggest that Period Four is very different from other periods, and future work should concentrate more on this period, not least because it accounted for the largest proportion of MVT. Further recommendations for policymakers will be provided in the following chapter based on the obtained results from the traditional regression and GWR models.

Overall, this chapter has highlighted the significance of the present study in detecting the changes in crime opportunities across the study area and throughout the day. A wide range of new findings discussed in this chapter have improved our understanding of MVT in SA and globally. The following chapter will summarise these key findings, presenting implications and reflections on current police practice and the limitations of this study.

Chapter 9

Conclusion and Policy Recommendations

9.1 Introduction

This study has addressed the substantial research gap in our understanding of the spatial-temporal patterns of motor vehicle theft (MVT) in Saudi Arabia (SA), in particular in Riyadh, where MVT is the prevalent property crime. This has been accomplished using routine activity theory (RAT) and crime pattern theory (CPT), the two major spatial crime theories, but theories developed in the West. Here, they have been applied to Saudi Arabia, testing their suitability for this very different cultural context. The assessment of the applicability of these theories in their application to a Saudi context is, in itself, another contribution by this study. Finally, the study extends more generally the knowledge and understanding of the settings of MVT, which differ considerably from other types of property crime that have been predominantly explained by environmental criminology theories. The goal of this chapter is to describe how the aim of this research, to understand MVT in SA, has been achieved. In addition, the chapter highlights the most important research findings and provides a number of recommendations and suggestions for policy and future research.

Section 9.2 begins by explaining how the objectives that were formulated in Chapter 1 have been met. The implications of this study for police practice are described in Section 9.3. Following this, Section 9.4 presents the key limitations of the research and a number of important implications for future research. The final Section 9.5 of the thesis contains the concluding remarks.

9.2 Summary of the Study Findings

The current study was designed to understand the phenomenon of MVT in SA, in particular in the capital city Riyadh, which has the highest rates of MVT amongst the cities in the Kingdom of Saudi Arabia. Thus, there is a demand for research to investigate this problem. As the spatial-temporal patterns of MVT in SA were under-researched, the study restricted its focus to addressing this substantial research gap. This was achieved using RAT and CPT, which have explained crime over space and time in the West (Felson and Clarke, 1998). However, as this study aimed to apply

RAT and CPT to the new context of SA and few of the existing MVT studies have applied these theories, a number of objectives were established to accomplish the major aim of this study. The following paragraphs summarise how these objectives have been met by outlining the key findings.

Objective One: To review environmental criminology theories and spatial analysis techniques to better understand the theory of how spatial crime patterns are generated.

Chapter 2 reviewed the key concepts of RAT and CPT and examined how these theories were developed to understand property crimes. The review revealed that these theories were developed within specific cultural, socio-economic and physical contexts, while their application generally focuses on burglary. The review indicated that RAT is represented by socioeconomic and demographic variables, as they reflect its elements of motivated offenders, suitable targets and absence of capable guardians. Meanwhile, CPT is represented by environmental features as these variables reflect its themes of crime attractors, generators, paths and activity nodes. Both RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) advance the idea that crime opportunities vary over space and time.

Having completed the review of these crime theories (RAT and CPT), Chapter 2 also examined the relevant spatial and statistical methods used to examine the aspects of the theories in order to achieve the above objective. The review highlighted two key aspects of the spatial analysis of crime that are aligned with the core theme of RAT and CPT: first, crime tends to concentrate at certain locations and during certain periods of time throughout the day; second, there are certain factors that contribute to these concentrations of crime. The review showed that the spatial exploratory methods represented in crime mapping techniques and spatial point pattern tests can be used to achieve the first aspect, whereas for the second aspect, the regression analysis methods are frequently used in the criminology field to identify the factors that contribute to these concentrations. The most popular regression methods used in different crime studies are ordinary least squares (OLS) and multinomial logistic (ML) regression at the global level. Two key aspects of spatial processes were identified: spatial heterogeneity and spatial dependence. Examining these is an essential step in fulfilling a spatial analysis of crime (Chainey and Ratcliffe, 2005). With regard to the first aspect of the spatial process – spatial dependence – the chapter reviewed the use of spatial autocorrelation as a measurement of spatial dependence, which can violate the assumptions of traditional regression models and confound their results. Thus, the use of GWR was reviewed as a spatial regression model to overcome the issue of existing spatial autocorrelation in regression model results, as well as detecting the spatial heterogeneity. Chapter 2 concluded by presenting the most important limitations of the spatial analysis methods. These include the Modifiable Areal Unit Problem (MAUP) (Ratcliffe, 2005; Fotheringham and Rogerson, 2004; Fotheringham and Rogerson, 1993) and the ecological fallacy (Wong, 2009; Chainey and Ratcliffe, 2005) highlighting that any study, as here, based on aggregating data at a geographical unit will suffer from these limitations.

Since RAT and CPT, which were developed in Western contexts, were applied in this study to explain MVT in Riyadh, the second objective was formulated as follows.

Objective Two: To compare the Saudi and Western contexts to identify any differences that could challenge the applicability of environmental criminology theories to the spatial analysis of MVT in Riyadh.

This objective was accomplished in Chapter 3, which explored the Saudi context, including demographic, social, economic, cultural and legal factors in comparison to the West. The key findings suggested that the SA context is very different from the Western context. A good illustration of these differences in demographics is the lower participation of females in the Saudi labour force, the large family size and younger population of SA. The differences apparent in the legal systems can be seen in the prohibition of drinking alcohol and the fact that woman are not allowed to drive in SA. Furthermore, there are differences in the built environment, as in SA private vehicles are the main form of transportation and houses are typically surrounded by high walls.

Furthermore, the findings of Chapter 3 in Section 3.3 revealed that the crime statistics in SA differ considerably from those in Western countries such as the US, the UK and Canada. MVT is a major problem in SA, particularly in Riyadh. It accounts for the majority of property crime in SA, whereas it comprises only a small proportion property crimes in the US, the UK and Canada. Identifying the extent of the differences between the two contexts and how MVT is a phenomenon in SA drove this study to propose the third objective as follows.

Objective Three: To critically review the crime literature on MVT in SA and the policing efforts to tackle MVT in order to identify how this thesis can contribute to the existing body of knowledge about crime, particularly MVT.

This objective was accomplished in Chapter 3 in Section 3.3. A review of the literature on crime in Saudi Arabia revealed that little research had been undertaken to understand crime from the perspective of geography. The existing studies reviewed suffered from a weak theoretical foundation and a lack of appropriate data and methods. More importantly, the review revealed that few studies have focused specifically on understanding the problem of MVT, and those that have predominantly focused on investigating the characteristics of car thieves (Al-Qahtani, 2008; Al Angari, 2002; Al-Otaibi, 2002; Al-Shaheen, 1996) rather than the more holistic picture offered by modern environmental criminology. Nevertheless, a key relevant finding of these studies was that vehicles parked outside victims' houses accounted for fewer thefts than those vehicles stolen from the street because they were left unattended with the engine running (Al Angari (2002).

Once the significant differences in the contexts were identified and the existing knowledge about MVT in SA was obtained, this led the research to ask how MVT has been studied in the West using the environmental criminology approach. Therefore, the following objective was proposed.

Objective Four: To critically review Western MVT studies contextualised within the frameworks of environmental criminology theories to identify influential factors on MVT that should be examined in the analysis of MVT in Riyadh.

The three major objectives achieved in Chapters 2 and 3 built up a comprehensive picture of the current theoretical and methodological frameworks of the analysis of crime patterns and the context of Saudi Arabia. However, the previous work should be linked to the empirical studies in order to investigate how these aspects were explicitly acknowledged and applied in Western criminology studies. Therefore, the objective stated above was addressed in Chapter 4. The key findings of the review indicated that few studies have attempted to contextualise MVT within the theoretical frameworks developed in environmental criminology (see Section 4.2). A key limitation of the existing studies that modelled MVT is that they failed to take into account that opportunities for crime vary over space and throughout the day. The review also highlighted a number of factors that are associated with MVT in the West, as well as contradictory findings which criticised these studies.

As MVT studies in the West were reviewed, Chapter 4 discussed the challenges that could limit the applicability of RAT and CPT in explaining MVT in SA. The challenges highlighted can be classified into two types: those related to the setting or dynamic of MVT as based on a movable object and those related to the characteristics of the Saudi context, which could play an important role in limiting the application of RAT and CPT, or would result in different findings to those found in Western studies. In terms of the nature or setting of MVT, an important challenge identified was the element of the absence of capable guardians. This was expected to be difficult to represent using socioeconomic and demographic variables. Furthermore, a significant finding of the evaluation of the theories suggested that RAT and CPT were based on the role of work, as there was a concentration of property crime during working hours, whereas MVT most often occurred during the night. With regard to the effect of contextual differences, the socioeconomic and demographic conditions that have contributed to high rates of property crime in the West include single adults living alone, females participating in the labour force, and a small household size. These are very different to the Saudi Arabian context. With regard to the effect of the physical environment, it is evident that in the case of the high walls surrounding houses, the occupants of houses in SA, such as housewives, were not expected to be able to play the role of capable guardians in preventing vehicle theft.

The chapter also showed that based on the themes of CPT, different patterns of criminogenic nodes and opportunities were expected in SA to those in the West due to differences in the built environment. A good illustration is the lack of footpaths in Riyadh neighbourhoods, with vehicles being the main form of transport for work and other daily evening activities to avoid the heat. From the discussion, it was expected that this contributes to fewer MVTs occurring near victims' homes during working hours and evening periods due to there being fewer targets available. MVT occurrence near victims' homes is most likely to be limited to sleeping hours when vehicles are parked outside on the street.

Chapter 4 contributed significantly to the achievement of objective four, as it highlighted a number of factors that have been found to influence the occurrence of MVT. In addition, the theoretical evaluation of the applicability of these theories identified several factors that could affect the results of examining MVT under RAT and CPT. This critical review of Western studies and the evaluation provided guidance for every aspect of the study's empirical work. The following objective was formulated as the first stage of the empirical work.

Objective Five: To explore the spatial patterns of MVT and detect significant differences in MVT across the study area and throughout the day in order to examine the first theme of RAT and CPT, which suggests that crime concentrates at certain places and during particular periods of the day.

The methodology and data used in order to achieve this objective were presented in Chapter 5. The MVT dataset was prepared for the analysis by dividing MVT incidents into four periods of the day representing the patterns of Saudi daily routines, according to RAT (Cohen and Felson, 1979) and CPT (Brantingham, P.L. et al., 2011; 2008; 1993) as described in Chapter 5. This is the first time that MVT has been divided into a number of time periods representing patterns of routine activities. The methods used to achieve this objective began with mapping using the quantile classification method, which has been found to be an appropriate method for making comparisons between maps (GeoSWG, 2012; Boba, 2005). This was used in this study to compare MVT rates during the four time periods of the day. Then, the spatial point pattern test was used to detect statistically significant differences between the spatial patterns of MVT that occurred in the four time periods. This objective aimed to examine the fundamental theme of RAT and CPT, which suggests that crime tends to concentrate at certain places and during particular times of the day, as explained in Chapter 2.

The results of applying these methods were presented in Chapter 6. The key finding that emerged in Chapter 6 was that each period was significantly different from the others (Section 6.3). However, the spatial patterns of MVT during Period Four exhibited a greater significant difference compared to the other periods. Overall, this significant difference between MVT occurrences from period to period strengthens the idea of RAT and CPT that crime opportunities vary over space and time stated above. The combination of these findings suggested that further investigation of the factors was essential to detect the cause of these variations in MVT throughout the day. Therefore, the following objective was proposed to identify these factors.

Objective Six: To predict and examine the relationship between MVT during four time periods throughout the day and a wide range of variables derived from RAT and CPT (and the integration of theories) that contribute to MVT concentration at certain places during particular time periods.

The achievement of this objective provided detailed understanding of the MVT problem in Riyadh through the use of the environmental criminology approach. The datasets and methods employed to conduct the analysis were presented in Chapter 5. The data were prepared for analysis on the basis of the theoretical framework developed for this study in the previous Chapters 2, 3 and 4. As explained earlier, MVT was divided into four periods of the day and the rates of MVT were calculated to represent the likelihood. The explanatory variables that represented the characteristics of Riyadh's neighbourhoods were prepared to reflect the themes of RAT and CPT. With the dataset prepared for analysis, the second Section 5.4.2 described how the regression analysis techniques were implemented to accomplish the sixth objective. Two levels of regression analysis were conducted. Ordinary least squares (OLS) and multinomial logistic (ML) models were used for the prediction of MVT at a global level, whereas geographically weighted regression (GWR) models were used to identify the relationships between MVT rates and predictors at the local level – (spatial heterogeneity) – and to account for spatial dependence amongst OLS residuals.

Chapter 5 explained how OLS regression models were run, taking into account several crucial assumptions. For example, principle component analysis (PCA) was used in order to combat the issue of multicollinearity and reduce the number of variables, as described in Section 5.4.2.2. Thereafter, both variables and components that were used to predict MVT rates were modelled using the OLS regression method. Furthermore, the second traditional regression method used in this study was the ML regression, as a different type of regression from the OLS regression. This regression model allowed for this study to identify and compare between significant explanatory factors with regard to their influences on the probability of MVT occurrences during the four time periods (in Section 5.4.2.4). As the ML regression models assume no high multicollinearity amongst variables, so only the components were used with the ML regression models. Assessment of spatial dependence is very important for spatial analysis (Chainey and Ratcliffe, 2005), as discussed in Chapter 2. The assumption of no spatial dependency amongst the residuals yielded from the regression models was tested using the global Moran's I. Chapter 5 explained that GWR was used in this study for two main purposes: to detect the effect of significant predictors on MVT rates at the local level – spatial heterogeneity, and also to overcome any existing spatial autocorrelation amongst residuals yielded from the OLS regression models. Chapter 7 presented the results from conducting these regression models.

In Chapter 7, a wide range of factors related to RAT, CPT and the integration of the theories that were statistically significant in predicting MVT throughout the day were presented and described. The results yielded from the OLS and the ML regression models agreed in showing that specific significant factors affected the occurrence of MVT during certain periods of the day. These results provide important insights into understanding the occurrence of MVT in Riyadh and the applicability of Western environmental criminology. One of the most important findings to emerge from this study is that certain factors contributed significantly to predicting MVTs in certain time periods, whereas they showed no significant predictive relationship with MVT at others.

Furthermore, the results of the global Moran's I test for residuals yielded from OLS regression models revealed important findings. For example, OLS regression models utilising RAT were able to explain the MVT rates during Periods One and Two, but did not explain the MVT rates well during Periods Three and Four. Whilst, the OLS regression models using CPT did not explain MVT rates well during any periods, since the residuals yielded from the regression models were clustered. However, the results showed an improvement in the models' performance after integration of the theories for MVT rates during Periods One, Two and Three. The OLS model for Period Four consistently did not explain the MVT rates well. The use of GWR in modelling with the integrated variables showed significant findings in the variations of the effect of coefficients on predicting MVT rates across the study area. Overall, Chapter 7 contributed significantly to the accomplishment of the sixth objective formulated in this study. It revealed crucial findings that were discussed in Chapter 8 in the context of the literature in this area.

The discussion of the results from the analysis in Chapter 8 revealed important findings. Here, in this conclusion chapter, the most important findings are summarised. They are classified into four major sections: findings that enhance the understanding of spatial patterns of MVT in SA in comparison to Western studies; findings that suggest an evaluation of the applicability of RAT and CPT; findings that provide implications for police practice (Section 9.3)'and findings with implications on current research practice (Section 9.4).

The most important findings that enhanced our understanding of MVT are summarised as follows:

The two issues that were proposed at the beginning of the thesis: the applicability of RAT and CPT to a non-Western setting, and MVT crimes, have been experienced and elucidated. The study found that the substantially different context of SA compared to the West, where the major environmental criminology theories originated, contributed considerably to the fact that some of the findings yielded are different from those in the West. Secondly, the findings of this study suggest that the nature (setting) of MVT, as based on a target that is movable, has played an important role in affecting the applicability of selected variables that represent RAT and CPT.

A good illustration of the effect of different contexts is the finding that suggests MVTs in SA, Riyadh were less likely to occur near the victims' homes, which is in contrast to the previous research of Western studies on MVT, in Canada (McCormick et al., 2007; Fleming et al., 1994), Sweden (Ceccato et al., 2002), the U.S. (Weisel et al., 2006; U.S. Department of Justice, 2000) and the U.K. (Clarke, R.V. and Mayhew, 1994). The present study has found that MVTs tended to be limited to occurring near the owner's home during sleeping hours. This is attributed to several reasons, such as the fact that there are no footpaths established in neighbourhoods and that vehicles are the main form of transport (see the discussion in Section 8.3). Furthermore, the study suggests that due to the cultural and climate difference, such as people in SA tending to leave vehicles unattended with the engine running and tending to drive to facilities to avoid heat, residential areas with a high population density and facilities are more likely to have a higher rate of MVT incidents, particularly during the evening. In terms of the differences in the built environment, as explained in Chapter 4, the percentage of housewives had no significant effect in predicting MVT. This result is more likely to be related to the architectural design of Saudi houses.

The second factor that has been considered in this study is the nature (setting) of MVT as a movable object. The most significant finding emerging from this study is that the explanatory factors fluctuate in their effects on MVT throughout the day, from a positive to a negative prediction, to having no effect, as a result of the variation in people's daily routines. This aspect was under-researched by previous studies modelling MVT, which treated these factors as having consistent influences throughout the day. In this study, for example, attractive places such as recreational and entertainment complexes had the greatest positive significant effect on MVT rates during the evening (representing CPT). Socioeconomic and demographic factors (representing RAT) explained the MVT variations well during Period One (sleeping hours) and Period Two (working hours). For example, areas with predominantly foreign workers tended to experience higher MVT rates during working hours – Period Two. This finding can be explained by the fact that these areas tended to be poor; more vehicles in these areas were available during working hours; vehicles owned by households within these areas were more likely not to have good security systems; and workers in these areas spent most of their time outside their homes. There is no suggestion in this thesis that foreign workers are inherently more likely to commit crime than Saudi nationals. During periods (One and Two), vehicles are more likely to be stationary. In contrast, these factors – (socioeconomic and demographic) – did not explain MVT well when vehicles tend to move from place to place during Periods Three and Four.

Objective Seven: To evaluate the applicability of the concepts of RAT and CPT outside their original contexts.

As discussed in Chapter 8, the findings of this study suggest that the variables proposed in Chapter 5 to measure the elements of RAT did not consistently contribute to increased MVT rates throughout the day. The findings showed that the factors representing elements of RAT vary temporally. For example, the routine household activities displayed significant predictive power for MVT rates during Period Two (6 am to 12 pm) working hours, whereas socioeconomic and demographic characteristics of neighbourhoods that represent motivated offenders made the greatest contributions to predicting MVT during Period One (12 am to 6 am). However, the findings of the present study provide no support for the variables used to measure the absence of capable guardians. This agrees with the findings of a number of previous studies that were unable to measure this element (Andresen, 2006b; Copes, 1999), bolstering claims that the element of the absence of capable guardians is difficult to determine for MVT using socioeconomic and demographic variables.

A vital finding of this study suggests that RAT provided the best explanation for MVT rates during Period Two (6 am to 12 pm), working hours. This could be attributed to the fact that RAT (and also CPT) were formulated based on the routines of working patterns. As is seen, RAT is able to explain burglaries, and burglaries occur most frequently during working hours. However, MVT is different because it tends to occur most frequently during the night both in the West and in SA. Therefore, the variables proposed to represent RAT offer less interpretation of MVT occurrences during Period Four – evening time – despite the fact that it accounts for the largest proportion of MVTs. This finding can be supported by findings from Western studies that showed MVT models using RAT also offer few insights into the causation of MVT in comparison to other crimes such as burglaries (see Section 8.2.4). Existing MVT studies have treated MVT in the same way as other types of property crimes in terms of explanatory variables. However, as this study showed, RAT variables worked better when vehicles were stationary, and when vehicles tended to be moved from place to place the variables presented under this theory showed less interpretive power.

With regard to the applicability of CPT, the findings suggest that although the factors used to represent CPT elements showed a greater fluctuation in their effects on MVT occurrences throughout the day compared with RAT variables, they did not provide as sufficient an explanation for MVTs as did the RAT factors during Periods One and Two. For example, the findings showed that the factors representing CPT indicated that the worst performance for modelling MVT rates occurred during sleeping hours. This is attributed to the fact that crime attractors and activities nodes have a low effect on attracting potential offenders and suitable targets at this time of night. This indicates that it was essential to combine CPT factors with socioeconomic and demographic variables (RAT variables), as has been done in this study (see Section 8.4).

Objective Eight: To provide recommendations to improve Saudi police practices to tackle MVT. This objective will be described in detail in the following section.

9.3 Policy Recommendations

In Chapter 3, the review of current police practice in SA indicated that several measures have been undertaken by Public Security – (the organisation tasked with maintaining public security) – to tackle this crime (Public Security, 2016; Public Security, 2012). These preventive measures ranged from improving cars' security systems to implementing some regulations at the local level, such as surveillance cameras to protect car facilities, or accelerating the effort of police in the field, such as increasing patrols in business districts. However, these policing efforts would be of greater help and more effective if they were concentrated and priority was given to those areas with specific characteristics that tend to experience MVTs at particular times. This has been overlooked by research in SA. This study provides new findings that can make a considerable contribution to the design of effective crime-prevention strategies in Riyadh, SA. The first recommendation is for the police to help reduce the MVT opportunities. According to the findings of this study, in particular from models of the integrated theories using GWR, the police should increase their patrol presence as shown in Table 9-1.

Table 9-1: Types of areas that are more vulnerable to MVT in certain neighbourhoods and at particular periods of time of the day

Types of areas	Most affected parts	Time Period
Deprived and poor areas	Eastern areas	12 am–6 am
Areas dominated by single people and youth	Southern areas	12 am–6 am
Areas dominated by foreign workers	Southern and central areas	6 am– 12 pm
Recreational and entertainment	Northern and eastern areas	6 pm – 12 am
Areas with high density of population and facilities densities	Central areas	6 pm -12 am

The second recommendation is to raise awareness of MVTs, showing the public when and where they are more likely to occur. The overall results indicate that vehicles in Riyadh tend to be stolen more frequently on the streets in areas where vehicles tend to be unattended while the engine is running. This finding should be used to increase people's awareness to secure their vehicles when they leave their vehicles—even if for few seconds. Furthermore, the results indicate that vehicles in residential areas are more vulnerable to being targeted by car thieves during sleeping hours. Thus, people within these areas should park their cars in their garages, if they are available, or use other vehicle security systems that have been effective in reducing MVT opportunities in the West, particularly in the UK (Morgan et al., 2016; Home Office, 2016; Farrell et al., 2011b). Moreover, areas with car facilities and car parks are more likely to have more MVTs during working hours. Hence, it is recommended to improve the security measures and regulations applied in these car facilities and car parks during working hours when there are more activities taking place at these sites. Based on the finding that vehicles parked in industrial areas for long hours during working time are more vulnerable for vehicle thefts, it is recommended that people who work in these areas should be aware of the risk of vehicle thefts.

9.4 Research Limitations and Future Work

Although this study has achieved its aim, there are several weaknesses that largely relate to the types of data and methods employed. The most important limitation lies in the fact that the datasets of this study were largely only available aggregated at a neighbourhood level. Consequently, some limitations are to be expected in this study. The most frequent limitations from using spatial methods based on aggregating data are the Modifiable Areal Unit Problem (MAUP) and the ecological fallacy, which were both described in Chapter 2 (see Section 2.3.3 for more details). Thus, for future work, MVT could be investigated at a lower geographical scale than neighbourhood level in order to reduce the effect of aggregating data on the results. However, in SA, the lowest geographical level at which census data can be obtained *is* at a neighbourhood level. This contrasts with Western countries, such as the UK, where census data are provided for very detailed geographic scales in which areas range in size from 40 households to 125 households (Office for National Statistics, 2017).

A second limitation is related to data availability. In this study, there were insufficient data available on some types of environmental features that can work as crime attractors, such as high schools and places of worship. A further limitation was the number of car parks used to estimate the density of car parking. It would have been more accurate if the density had been determined using the actual capacity of these car parks rather than their mere presence. Furthermore, the poverty factor was estimated using unemployment rates and low or no education qualifications (LNEQ). It would have been helpful if this variable had been measured using official national indicators for poverty, but these could not be obtained by this study.

The results from OLS regression models, in which the rates of MVT were being used as a dependent variable, are almost in line with those results obtained from ML regression models, in which MVT incidents were measured at the nominal level with four categories of responses. However, MVT is based on non-stationary objects which are subject to change in the density of vehicles within neighbourhoods by the hour.

This could have an effect on the measurement of MVT rates using vehicle ownership within neighborhoods. Specifically, during the times of the day when vehicles are more likely to move from one place to another. There was expected to be an increase of vehicles coming from outside these neighbourhoods during certain times. Thus, future research could take into account the traffic volume on the roads to measure the availability of vehicles (targets) on the roads at different time periods. For example, traffic volume by hour across the city could be used when calculating MVT rates.

As with many other environmental criminology studies that use census data (Roberts and Block, 2012; Cahill and Mulligan, 2007; Andresen, 2006a; Andresen, 2006b; Weisel et al., 2006; Rice and Smith, 2002; Copes, 1999; Messner and Blau, 1987), this research used the characteristics of neighbourhoods to measure the absence of capable guardians, and the presence of motivated offenders and suitable targets. An improvement would be to obtain more information on the daily routines of arrested car thieves and victims of vehicle thefts. This would help future research to determine factors that can contribute to MVT occurrences, which have not yet been examined by existing studies.

The significance of this study in examining MVTs at four time periods of the day is that it has provided insight into the variations in the ability of explanatory factors to predict MVTs throughout the day. The results from the OLS and GWR regression models suggest that MVTs that occur during Period Four require further investigation in order to obtain a greater understanding of the spatial factors behind MVTs during this period. This has an important implication for future research on MVT, not only in SA, but also at a criminology research level to give greater focus on the period of highest frequency of MVT. Furthermore, the findings of this study revealed how MVTs varied throughout the day as a result of changes in routine daily activities, and further research could thus usefully explore the impacts of daily events on MVT incident patterns, such as religious events.

This study has not covered some aspects of the spatial analysis of MVT, which were beyond its scope, however, these could be investigated in future research. For example, this study could be repeated using MVT data divided on the basis of the motivation of theft into temporary ("joyriding" style) and permanent MVT. Furthermore, another possible area of work would be to investigate the relationship between recovery locations and theft locations, which could help the police to predict which areas may be prone to stolen vehicles and recovery. A final recommendation, in terms of the applicability of RAT and CPT, is that it would be interesting to compare the findings of this study with the applicability of these theories to explain burglary in SA.

9.5 Concluding Remarks

This study has analysed the spatial patterns of MVT under RAT and CPT in order to understand the problem of MVT in SA, in particular in Riyadh. Although this study has some limitations relating to the type of spatial data and methods, the very latest data obtained and the sophisticated techniques used have improved our understanding of MVT in SA. A wide range of crucial findings have been yielded from this study and these can contribute considerably to improving the current crime prevention and reduction strategies. In addition, these findings have important implications for the understanding of MVT and any property crime, when taking into consideration the variations in the opportunities for crime across the study area, throughout the day and the setting or behaviour for any crime.

List of References

Aasi, G.H. 2003. Islamic legal and ethical views on organ transplantation and donation. *Zygon®.* **38**(3), pp.725-734.

Ackerman, W.V. and Murray, A.T. 2004. Assessing spatial patterns of crime in Lima, Ohio. *Cities.* **21**(5), pp.423-437.

Akpinar, E. and Usul, N. 2004. Geographic Information Systems Technologies in Crime Analysis and Crime Mapping. *proceedings. ESRI.*

Al Angari, S.A. 2002. *Motor Vehicle Theft Crimes in the Kingdom of Saudi Arabia.(In Arabic).* Riyadh, Saudi Arabia: Ministry of Interior, Crime Prevention Research Centre.

Al-Bashar, K. 2001. *crime prevention in the Kingdom of Saudi Arabia.(In Arabic).* Saudi Arabia: The Saudi Dar

Al-Bashari, M.A.-A. 1999. *Crime Patterns in the Arab World. (In Arabic).* Riyadh, Saudi Arabia: Naif Arab University For Security Sciences

Al-Khalifah, A.H. 1994. Religiosity in Islam as a protective mechanism against criminal temptation. *The American Journal of Islamic Social Sciences.* **11**(1), pp.1-11.

Al-Khalifah, A.H. 1997. *The social constraints for crime distribution in Riyadh.(In Arabic).* Riyadh: Crime Prevention Research Centre

Al-Kharif, R. 1998. *Crime in Saudi cities.(In Arabic)* Riyadh, Saudi Arabia: Crime Prevention Research Centre

Al-Otaibi, M.D. 2002. *Secondary School Student's Tendencies toward Car Theft.(In Arabic).* Master thesis, Naif Arab University for Security Sciences.

Al-Qahtani, D.N. 2008. *The social and economic characteristics of juveniles who steal cars.(In Arabic).* Master thesis, Naif Arab University for Security Sciences.

Al-Shaheen, A.M. 1996. *The Factors Accompanying Car Stealing Committed By Juveniles.(In Arabic).* Master thesis, Naif Arab University for Security Sciences.

Aldawsari, I. 1997. *The spatial distribution of crime in Jeddah and examining social, economic and educational characteristics of criminal prisoners in Jeddah's prison.(In Arabic).* Riyadh: Crime Prevention Research Centre

Aldstadt, J. 2010. Spatial clustering. *Handbook of applied spatial analysis.* Springer, pp.279-300.

AlMarzougi, H., Al-Ghamdi, A. and Alsyad, A. 1986. *The relationship between social, family, educational and economical characteristics of prisoners who* *are non-drug offenders nd their relation to types of crime in the Kingdom of Saudi Arabia.* Riyadh: Crime Prvention Research Centre.

Almatrafi, M. 2005. *Geography of theft crime in Makkah. (In Arabic)*. Master thesis, Umm Al qura University (Unpublished).

Almeida, E.S., Haddad, E.A. and Hewings, G.J. 2005. The spatial pattern of crime in Minas Gerais: An exploratory analysis. *Economia Aplicada.* **9**(1), pp.39-55.

Alotaibi, N. 2016. *Street view with parked cars and houses, Saudi Arabia, Riyadh.* . Riyadh, Saudi Arabia: Unpublished photograph.

Alotaibi, N. 2017a. *A street view of a residential area in Riyadh, Saudi Arabia.* Riyadh, Saudi Arabia: Unpublished photograph.

Alotaibi, N. 2017b. *Street view with shops, grocery stores, restaurants and offices distributed along the street of a residential area in Saudi Arabia, Riyadh.* Riyadh, Saudi Arabia: Unpublished photograph.

Alwelaie, A. 1993. *Theft crime in Riyadh City; an analytic study of geography of crime.(In Arabic).* Riyadh: Centre for Crime Prevention, Minstry of interior of Saudi Arabia.

Andresen, M.A. 2006a. Crime measures and the spatial analysis of criminal activity. *British Journal of criminology.* **46**(2), pp.258-285.

Andresen, M.A. 2006b. A spatial analysis of crime in Vancouver, British Columbia: a synthesis of social disorganization and routine activity theory. *The Canadian Geographer/Le Géographe canadien.* **50**(4), pp.487-502.

Andresen, M.A. 2009. Testing for similarity in area-based spatial patterns: a nonparametric Monte Carlo approach. *Applied Geography.* **29**(3), pp.333-345.

Andresen, M.A. 2010. The place of environmental criminology within criminological thought. *Classics in environmental criminology.* pp.9-28.

Andresen, M.A. 2014. *Environmental Criminology: Evolution, Theory, and Practice.* Routledge.

Andresen, M.A. 2015. Predicting Local Crime Clusters Using (Multinomial) Logistic Regression. *Cityscape.* **17**(3), p249.

Andresen, M.A. 2016. An area-based nonparametric spatial point pattern test: The test, its applications, and the future. *Methodological Innovations.* **9**, p2059799116630659.

Andresen, M.A., Brantingham, P.J. and Kinney, J.B. 2010. *Classics in environmental criminology.* CRC Press.

Andresen, M.A. and Jenion, G.W. 2004. The unspecified temporal criminal event: What is unknown is known with aoristic analysis and multinomial logistic regression. *Western Criminology Review.* **5**(3), pp.1-11.

Andresen, M.A. and Linning, S.J. 2012. The (in) appropriateness of aggregating across crime types. *Applied Geography*. **35**(1), pp.275-282.

Andresen, M.A., Linning, S.J. and Malleson, N. 2016. Crime at places and spatial concentrations: exploring the spatial stability of property crime in Vancouver BC, 2003–2013. *Journal of Quantitative Criminology*. pp.1-21.

Andresen, M.A. and Malleson, N. 2010. Testing the stability of crime patterns: implications for theory and policy. *Journal of Research in Crime and Delinquency*. p0022427810384136.

Andresen, M.A. and Malleson, N. 2013. Crime seasonality and its variations across space. *Applied Geography*. **43**, pp.25-35.

Anselin, L. 2001. Spatial econometrics. In: Baltagi, B.H. ed. *A companion to theoretical econometrics.* Blackwell

Anselin, L., Cohen, J., Cook, D., Gorr, W. and Tita, G. 2000. Spatial analyses of crime. *Criminal justice.* **4**, pp.213-262.

Anselin, L. and Getis, A. 1992. Spatial statistical analysis and geographic information systems. *The Annals of Regional Science.* **26**(1), pp.19-33.

Anselin, L., Griffiths, E. and Tita, G. 2008. 6. Crime mapping and hot spot analysis. *Environmental criminology and crime analysis.* p97.

Australian Institute of Criminology. 2003. *Crimes Facts Info, Reporting Crime to Police.* Australian Institute of Criminology.

Barkan, S.E. and Bryjak, G.J. 2011. *Fundamentals of criminal justice: A sociological view.* Jones & Bartlett Publishers.

Beavon, D.J., Brantingham, P.L. and Brantingham, P.J. 1994. The influence of street networks on the patterning of property offenses. *Crime prevention studies.* **2**, pp.115-148.

Benjanuvatra, S. 2013. QML Estimation of the Spatial Weight Matrix in the MR-SAR Model. In: *VII World Conference of the Spatial Econometrics Association, Washington DC, USA.*

Bernasco, W. and Elffers, H. 2010. Statistical analysis of spatial crime data. *Handbook of quantitative criminology*. Springer, pp.699-724.

Block, R. 1979. Community, environment, and violent crime. *Criminology.* **17**(1), pp.46-57.

Boba, R. 2005. *Crime analysis and crime mapping.* 3 ed. Thousand Oaks, CA: SAGE Publications.

Boggs, S.L. 1965. Urban crime patterns. *American Sociological Review.* pp.899-908.

Braga, A.A. 2001. The effects of hot spots policing on crime. *The ANNALS of the American Academy of Political and Social Science.* **578**(1), pp.104-125.

Brantingham, P.J. and Brantingham, P.L. 1993. Environment, routine and situation: Toward a pattern theory of crime. *Advances in criminological theory.* **5**, pp.259-294.

Brantingham, P.J. and Brantingham, P.L. 2008. 5. Crime pattern theory. *Environmental criminology and crime analysis.* p78.

Brantingham, P.L. and Brantingham, P.J. 1981. Notes on the geometry of crime. *Environmental criminology.* **1981**, pp.27-54.

Brantingham, P.L. and Brantingham, P.J. 1993b. Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology.* **13**(1), pp.3-28.

Brantingham, P.L. and Brantingham, P.J. 1995. Criminality of place. *European Journal on Criminal Policy and Research.* **3**(3), pp.5-26.

Brantingham, P.L. and Brantingham, P.J. 1998. Mapping crime for analytic purposes: location quotients, counts, and rates. *Crime mapping and crime prevention.* **8**, pp.263-288.

Brantingham, P.L., Wuschke, K., Frank, R. and Brantingham, P.J. 2011. Crime Emergence and Simulation Modeling: Modeling crime space. In: C. Sullivan, et al. eds. *Crime emergence: Reducing uncertainty in theory and research.* Routledge.

Brauer, J.R., Antonaccio, O. and Tittle, C.R. 2013. Does Religion Suppress, Socialize, Soothe, or Support? Exploring Religiosity's Influence on Crime. *Journal for the Scientific Study of Religion.* **52**(4), pp.753-774.

Brewer, C.A. and Suchan, T.A. 2001. *Mapping Census 2000: The geography of US diversity.* ESRI, Inc.

Britt, C.L. and Weisburd, D. 2010. Logistic regression models for categorical outcome variables. *Handbook of quantitative criminology.* Springer, pp.649-682.

Bruna, F. and Yu, D. 2013. Geographically weighted panel regression. In: *XI Congreso Galego de Estatística e Investigación de Operacións.*

Brunsdon, C., Corcoran, J. and Higgs, G. 2007. Visualising space and time in crime patterns: A comparison of methods. *Computers, Environment and Urban Systems.* **31**(1), pp.52-75.

Brunsdon, C., Fotheringham, A.S. and Charlton, M.E. 1996. Geographically weighted regression: a method for exploring spatial nonstationarity. *Geographical analysis.* **28**(4), pp.281-298.

Bryant, C.D. 2012. *Routledge Handbook of Deviant Behavior.* Taylor & Francis.

Cahill, M. and Mulligan, G. 2007. Using geographically weighted regression to explore local crime patterns. *Social Science Computer Review.* **25**(2), pp.174-193.

Canter, P. 2000. Using a geographic information system for tactical crime analysis. *Analyzing crime patterns: Frontiers of practice.* pp.3-10.

Ceccato, V. 2009. Crime in a city in transition: the case of Tallinn, Estonia. *Urban Studies.* **46**(8), pp.1611-1638.

Ceccato, V., Haining, R. and Signoretta, P. 2002. Exploring offence statistics in Stockholm City using spatial analysis tools. *Annals of the Association of American Geographers.* **92**(1), pp.29-51.

Central Department of Statistics and Information. 2007. *Population&Housing.* Saudi Arabia.

Central Department of Statistics and Information. 2008a. *Demographic Survey of Saudi Arabia.* Saudi Arabia Central Department of Statistics and Information.

Central Department of Statistics and Information. 2008b. *Labour Force in Saudi Arabia.* Saudi Arabia: Central Department of Statistics and Information.

Central Department of Statistics and Information. 2009. *Labour Force in Saudi Arabia.* Saudi Arabia, Riyadh: Central Department of Statistics and Information.

Central Department of Statistics and Information. 2010. *Statistical Yearbook.* Saudi Arabia, Riyadh: Central Department of Statistics and Information.

Central Department of Statistics and Information. 2012. *Statistical Yearbook 2012.* Saudi Arabia, Riyadh: Central Department of Statistics and Information.

Chainey, S. and Ratcliffe, J. 2005. *GIS and crime mapping.* England: John Wiley & Sons.

Chakraborty, S., & Pelfrey, W. ed. 2000. *Exploratory data analysis of crime patterns: Preliminary findings from the Bronx.* Thousand Oaks, CA: SAGE Publications.

Challinger, D. 1987. Car security hardware-how good is it? In: *Proceedings of Seminar on Car Theft*: National Roads and Motorists' Association and the Australian Institute of Criminology.

Chang, D. 2011. Social crime or spatial crime? Exploring the effects of social, economical, and spatial factors on burglary rates. *Environment and Behavior.* **43**(1), pp.26-52.

Chaplin, R., Flatley, J. and Smith, K. 2011. Crime in England and Wales 2010/11: findings from the British Crime Survey and police recorded crime. *Home Office: London.*

Charlton, M. and Fotheringham, A. 2009. *Geographically Weighted Regression: A Tutorial on Using GWR in ArcGIS 9.3.*: National Centre for Geocomputation. National University of Ireland. Available from: http://www.geos.ed.ac.uk/~gisteac/fspat/gwr/gwr_arcgis/GWR_Tutorial.pdf

Chen, X., Ender, P.B., Mitchell, M. and Wells, C. 2013. *Stata web books: regression with Stata*. Academic Technology Services., URL http://www. ats. ucla. edu/stat/stata/webbooks/reg/default. htm-(retrieved: 20.12. 2006).

CIA. 2016. *The World Factbook, Age Structure.* [Online]. [Accessed 15 May 2017]. Available from: https://www.cia.gov/library/publications/the-world-factbook/fields/2010.html

Clarke, R.V. 1997. *Situational crime prevention.* Criminal Justice Press.

Clarke, R.V. 1999. *Hot products: understanding, anticipating and reducing demand for stolen goods*. Home Office, Policing and Reducing Crime Unit, Research, Development and Statistics Directorate.

Clarke, R.V. 2002. *Thefts of and from Cars in Parking Facilities.* US Department of Justice, Office of Community Oriented Policing Services.

Clarke, R.V. and Cornish, D.B. 1985. Modeling offenders' decisions: A framework for research and policy. *Crime and justice.* **6**, pp.147-185.

Clarke, R.V. and Harris, P.M. 1992. Auto theft and its prevention. *Crime and Justice.* pp.1-54.

Clarke, R.V. and Mayhew, P. 1994. Parking patterns and car theft risks: Policy-relevant findings from the British Crime Survey. *Crime prevention studies.* **3**, pp.91-107.

Clarke, S. 2013. *Trends in crime and criminal justice, 2010.* [Online]. [Accessed 10 May 2014]. Available from: http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-SF-13-018/EN/KS-SF-13-018-EN.PDF

Cohen, L.E. and Felson, M. 1979. Social change and crime rate trends: A routine activity approach. *American sociological review.* pp.588-608.

Cohen, L.E., Felson, M. and Land, K.C. 1980. Property crime rates in the United States: A macrodynamic analysis, 1947-1977; with ex ante forecasts for the mid-1980s. *American journal of Sociology.* pp.90-118.

Cohen, L.E., Kluegel, J.R. and Land, K.C. 1981. Social inequality and predatory criminal victimization: An exposition and test of a formal theory. *American Sociological Review.* pp.505-524.

Compton, G. 2013. *Population and Household Estimates for the United Kingdom, March 2011.* United Kingdom: Office for National Statistics.

Congdon, P.D. 2013. A model for spatially varying crime rates in English districts: the effects of social capital, fragmentation, deprivation and urbanicity. *International journal of criminology and sociology.* **2**, p138.

Copes, H. 1999. Routine activities and motor vehicle theft: A crime specific approach. *Journal of Crime and Justice.* **22**(2), pp.125-146.

Cornish, D.B. and Clarke, R.V. 1987. Understanding crime displacement: An application of rational choice theory. *Criminology*. **25**(4), pp.933-948.

Cornish, D.B. and Clarke, R.V. 2008. 2. The rational choice perspective. *Environmental criminology and crime analysis.* p21.

Cozens, P.M., Saville, G. and Hillier, D. 2005. Crime prevention through environmental design (CPTED): a review and modern bibliography. *Property management.* **23**(5), pp.328-356.

Dauvergne, M. 2008. Motor vehicle theft in Canada, 2007. *Juristat*
. **28**(10).

David, P.R. and Scott, J.W. 1973. A crosscultural comparison of juvenile offenders, offenses, due processes, and societies: The Cases of Toledo, Ohio, and Rosario, Argentina. *Criminology.* **11**(2), pp.183-205.

de Melo, S.N., Matias, L.F. and Andresen, M.A. 2015. Crime concentrations and similarities in spatial crime patterns in a Brazilian context. *Applied Geography.* **62**, pp.314-324.

Department for Transport. 2016. *Road Traffic Estimates: Great Britain 2015.* UK: Department for Transport.

Desmond, S.A., Kikuchi, G. and Morgan, K.H. 2010. Congregations and Crime: Is the Spatial Distribution of Congregations Associated with Neighborhood Crime Rates? *Journal for the scientific study of religion.* **49**(1), pp.37-55.

Devery, C. 1993. Patterns of motor vehicle theft. *New South Wales Bureau of Crime Statistics and Research, Australia.*

Drugs and Crime Prevention Committee. 2002. *Inquiry into Motor Vehicle Theft, Final Report.* Australia: Parliament of Victoria & Drugs and Crime Prevention Committee.

Du, J., Park, Y.-T., Theera-Ampornpunt, N., McCullough, J.S. and Speedie, S.M. 2012. The use of count data models in biomedical informatics evaluation research. *Journal of the American Medical Informatics Association.* **19**(1), pp.39-44.

Eberts, P. and Sehwirian, K.P. 1968. Metropolitan Crime Rates and Relative Deprivation†. *Criminology.* **5**(4), pp.43-52.

Eck, J.E., Chainey, S., Cameron, J. and Wilson, R. 2005. *Mapping crime: Understanding hotspots.* Washington DC.: National Institute of Justice.

Eck, J.E., Gersh, J.S. and Taylor, C. 2000. Finding crime hot spots through repeat address mapping. In: Goldsmith, V., et al. eds. *Analyzing Crime Patterns: Frontiers of Practice* Thousand Oaks, CA: Sage Publications., pp.49–64.

Eck, J.E. and Weisburd, D. 1995. Crime places in crime theory. *Crime and place, crime prevention studies.* **4**, pp.1-33.

European Communities. 2004. A review of scientifically evaluated Good practices for reducing feelings of insecurity or fear of crime in the Eu member states . [Online]. pp.1-62. [Accessed 22 March 2014]. Available from: http://www.eucpn.org/pubdocs/review_reducing_feelings_insecurities_fear_crime_en.pdf

Fabrigar, L.R., Wegener, D.T., MacCallum, R.C. and Strahan, E.J. 1999. Evaluating the use of exploratory factor analysis in psychological research. *Psychological methods.* **4**(3), p272.

Farrell, G., Tilley, N., Tseloni, A. and Mailley, J. 2011a. The crime drop and the security hypothesis. *Journal of Research in Crime and Delinquency.* **48**(2), pp.147-175.

Farrell, G., Tseloni, A. and Tilley, N. 2011b. The effectiveness of vehicle security devices and their role in the crime drop. *Criminology and Criminal Justice.* **11**(1), pp.21-35.

FBI. 2013. *Crime in the United States by Volume and Rate per 100,000 Inhabitants, 1993–2012.* Washington, D.C: U.S. Department of Justice—Federal Bureau of Investigation.

FBI. 2016. *Crime in the United States, 2015.* Washington, D.C: U.S. Department of Justice—Federal Bureau of Investigation.

Federal Bureau of Investigation. 2004. *Uniform Crime Reporting Handbook.* Washington, D.C: U.S. Dept. of Justice, Federal Bureau of Investigation.

Ten-Year Arrest Trends. 2011a. [Online database]. United States: U.S. Dept. of Justice, Federal Bureau of Investigation.

Federal Bureau of Investigation. 2011b. *Uniform Crime Report, Crime in the United States.* United States: U.S. Department of Justice.

Federal Bureau of Investigation. 2012a. *Offenses Cleared.* United States: U.S. Dept. of Justice, Federal Bureau of Investigation.

Federal Bureau of Investigation. 2012b. *Uniform Crime Reports-Property crime.* [Online]. [Accessed 15 March 2016]. Available from: https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2012/crime-in-the-u.s.-2012/property-crime/property-crime

Felson, M. 1986. Linking criminal choices, routine activities, informal control, and criminal outcomes. *The reasoning criminal.* Springer, pp.119-128.

Felson, M. and Boivin, R. 2015. Daily crime flows within a city. *Crime Science.* **4**(1), p31.

Felson, M. and Clarke, R.V. 1998. Opportunity makes the thief. *Police research series, paper.* **98**.

Felson, M. and Poulsen, E. 2003. Simple indicators of crime by time of day. *International Journal of Forecasting.* **19**(4), pp.595-601.

Feng, Y. and Luo, J. 2016. When Do Luxury Cars Hit the Road? Findings by A Big Data Approach *eprint arXiv:1605.02827.* [Online]. Available from: https://arxiv.org/pdf/1605.02827.pdf

Ferreira, J., João, P. and Martins, J. 2012. GIS for Crime Analysis-Geography for Predictive Models. *The Electronic Journal Information Systems Evaluation.* **15**(1).

Field, A. 2009. *Discovering statistics using SPSS.* Sage publications.

Filbert, K. 2008. Targeting crime in hot spots and hot places. *Geography & Public Safety.* **1**(1), pp.4-7.

Fleisher, B.M. 1963. The effect of unemployment on juvenile delinquency. *The Journal of Political Economy.* **71**(6), pp.543-555.

Fleming, Z., Brantingham, P. and Brantingham, P. 1994. Exploring auto theft in British Columbia. *Crime prevention studies.* **3**, pp.47-90.

Flowers, A.S. 2006a. *Fact Sheet: Motor Vehicle Theft in the District of Columbia.* Institute for Public Safety & Justice University of the District of Columbia.

Flowers, A.S. 2006b. *A Spatial Temporal Analysis of Motor Vehicle Theft in the District of Columbia.* University of the District of Columbia: Institute for Public Safety & Justice.

Fotheringham, S. and Rogerson, P. 1993. GIS and spatial analytical problems. *International Journal of Geographical Information Science.* **7**(1), pp.3-19.

Fotheringham, S. and Rogerson, P. 2004. *Spatial analysis and GIS.* CRC Press.

Freedom To Marry. 2016. *The Freedom to Marry Internationally.* [Online]. [Accessed 1 May 2016]. Available from: http://www.freedomtomarry.org/pages/the-freedom-to-marry-internationally

Fujita, S. 2010. Risk Factors for Auto Theft. *Research Brief Series Dedicated to Shared Knowledge.* **3**, pp.1-3.

GeoSWG. 2012. *Cartographic guidelines for public health.* Centers for Disease Control and Prevention.

Getis, A. 1999. Spatial statistics. *Geographical information systems.* **1**, pp.239-251.

Getis, A. 2010. Spatial autocorrelation. *Handbook of Applied Spatial Analysis.* Springer, pp.255-278.

Goodchild, M.F. and Haining, R.P. 2004. GIS and spatial data analysis: Converging perspectives. *Papers in Regional Science.* **83**(1), pp.363-385.

Grabosky, P.N. 1995. *Burglary prevention.* Australian Institute of Criminology Canberra.

Greenberg, S.W. and Rohe, W.M. 1984. Neighborhood Design and Crime A Test of Two Perspectives. *Journal of the American Planning Association.* **50**(1), pp.48-61.

Gunnoe, M.L. and Moore, K.A. 2002. Predictors of religiosity among youth aged 17–22: A longitudinal study of the National Survey of Children. *Journal for the Scientific Study of Religion.* **41**(4), pp.613-622.

Hakim, S. and Gaffney, M. 1995. Residential burglary patterns. *Locksmith Ledger Dated.* pp.66-87.

Hannon, L. and DeFronzo, J. 1998. Welfare and property crime. *Justice Quarterly.* **15**(2), pp.273-288.

Harlow, C.W. 1988. *Motor vehicle theft.* US Department of Justice, Bureau of Justice Statistics Washington, DC.

Harrendorf, S., Heiskanen, M. and Malby, S. 2010. *International statistics on crime and justice.* European Institute for Crime Prevention and Control, affiliated with the United Nations (HEUNI).

Harries, K.D. 1973. *The geography of crime and justice.* McGraw-Hill.

Heck, R.H., Thomas, S. and Tabata, L. 2013. *Multilevel modeling of categorical outcomes using IBM SPSS.* Routledge Academic.

Henry, L.M. and Bryan, B.A. 2000. Visualising the spatio-temporal patterns of motor vehicle theft in Adelaide, South Australia. In: *Post Graduate Diploma Student, September 2000, GISCA National Key Centre for Social Applications of GIS Lecturer, GISCA National Key Centre for Social Applications of GIS*.

Higgins, K. 1997. *Exploring motor vehicle theft in Australia.* Australia: Australian Institute of Criminology Canberra.

Higgins, N., Robb, P. and Britton, A. 2009. Geographic patterns of crime. *Crime in England and Wales.* **10**, pp.165-194.

High Commission for Development of Riyadh. 2009. *Investment climate in Riyadh City* Riyadh: High Commission for Development of Riyadh.

High Commission for Development of Riyadh. 2012. *Environmental Features for Riyadh, Datasets*. Unpublished.

Hipp, J.R. 2007. Block, tract, and levels of aggregation: neighborhood structure and crime and disorder as a case in point. *American Sociological Review.* **72**(5), pp.659-680.

Hirschfield, A. and Bowers, K.J. 1997. The effect of social cohesion on levels of recorded crime in disadvantaged areas. *Urban Studies.* **34**(8), pp.1275-1295.

Hodgkinson, T., Andresen, M.A. and Farrell, G. 2016. The decline and locational shift of automotive theft: A local level analysis. *Journal of Criminal Justice.* **44**, pp.49-57.

Home Office. 2012. *A summary of recorded crime data from 1898 to 2001/02.* England and Wales: Home Office.

Home Office. 2014. *Vehicle Offences.* UK.

Home Office. 2016. *Modern Crime Prevention Strategy.* Home Office.

Howden, L.M. and Meyer, J.A. 2010. Age and sex composition: 2010. *2010 Census Briefs, US Department of Commerce, Economics and Statistics Administration. US CENSUS BUREAU.*

Ḥumayd, A.A.S. 1979. *Islamic criminal law: a comparative study between Islamic criminal law and positive laws.* Saudi Arabia: Dār Ṭuwyaq.

Hutcheson, G.D. and Sofroniou, N. 1999. *The multivariate social scientist: Introductory statistics using generalized linear models.* Sage.

Jackson, J.E. 2005. *A user's guide to principal components.* Canada: John Wiley & Sons.

Jansson, K. and Britain, G. 2007. *British Crime Survey-measuring crime for 25 years.* Home Office London.

Jeffery, C.R. 1959. Historical Development of Criminology. *J. Crim. L. & Criminology.* **50**, p3.

Jeffery, C.R. 1971. *Crime Prevention Through Environmental Design.* Beverly Hills, CA: Sage.

Jetmore, L.F. 2007. *Path of the hunter: Entering and Excelling in the Field of Criminal Investigation.* Looseleaf Law Publications.

Kapland, H., O'kane, K., Lavrakas, P. and Pesce, E. 1978. *Crime prevention through environmental design: final report on commercial demonstration, Portland, Oregon may 1978.* United States of America: National Institute of Justice.

Kennedy, L.W. and Forde, D.R. 1990. Routine activities and crime: An analysis of victimization in Canada. *Criminology.* **28**, p137.

Kinney, J.B., Brantingham, P.L., Wuschke, K., Kirk, M.G. and Brantingham, P.J. 2008. Crime attractors, generators and detractors: land use and urban crime opportunities. *Built environment.* **34**(1), pp.62-74.

Landau, S. and Everitt, B. 2004. *A handbook of statistical analyses using SPSS.* Chapman & Hall/CRC Boca Raton, FL.

Laurence, J. and Bentley, L. 2016. Does ethnic diversity have a negative effect on attitudes towards the community? A longitudinal analysis of the causal claims within the ethnic diversity and social cohesion debate. *European Sociological Review.* **32**(1), pp.54-67.

Leech, N.L., Barrett, K.C. and Morgan, G.A. 2005. *SPSS for intermediate statistics: Use and interpretation.* Psychology Press.

Leech, N.L., Barrett, K.C. and Morgan, G.A. 2014. *IBM SPSS for intermediate statistics: Use and interpretation.* Routledge.

Leung, Y., Mei, C.-L. and Zhang, W.-X. 2000. Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A.* **32**(1), pp.9-32.

Lewsey, J. 2006. Medical Statistics: A Guide to Data Analysis and Critical Appraisal. *Annals of The Royal College of Surgeons of England.* **88**(6), p603.

Lin, C.-H. and Wen, T.-H. 2011. Using geographically weighted regression (GWR) to explore spatial varying relationships of immature mosquitoes and human densities with the incidence of dengue. *International journal of environmental research and public health.* **8**(7), pp.2798-2815.

Lockwood, B. 2012. The presence and nature of a near-repeat pattern of motor vehicle theft. *Security Journal.* **25**(1), pp.38-56.

Lofquist, D., Lugaila, T., O'Connell, M. and Feliz, S. 2012. *Households and families: 2010.* US.

Lowman, J. 1986. Conceptual issues in the geography of crime: Toward a geography of social control. *Annals of the Association of American Geographers.* **76**(1), pp.81-94.

Lu, Y. 2006. Spatial choice of auto thefts in an urban environment. *Security Journal.* **19**(3), pp.143-166.

Lyons, D. and Teigen, A. 2008. Auto Theft Prevention. In: *NatioNal CoNfereNCe of State legiSlatureS, Washington, D.C.* .

Mackie, P., Laird, J. and Johnson, D. 2012. Buses and economic growth: main report. *Institute for Transport Studies.* http://www. *greenerjourneys. com/2012/07/buses-economic-growth-making-the-link-new-report.*

Mahya, N. 2003. *The relationship between crime rates and growth and density of population of Riyadh at police district levels. (In Arabic)*. Master thesis, Naif Arab University for Security Sciences (Unpublished).

Malczewski, J. and Poetz, A. 2005. Residential Burglaries and Neighborhood Socioeconomic Context in London, Ontario: Global and Local Regression Analysis*. *The Professional Geographer.* **57**(4), pp.516-529.

Malleson, N. and Andresen, M.A. 2015. Spatio-temporal crime hotspots and the ambient population. *Crime Science.* **4**(1), pp.1-8.

Maltz, M.D. 1994. Deviating from the mean: The declining significance of significance. *Journal of research in crime and delinquency.* **31**(4), pp.434-463.

Maltz, M.D. 1995. Criminality in space and time: Life course analysis and the micro-ecology of crime. *Crime and Place, Criminal Justice Press, Monsey, New York.*

Mateu, J. and Müller, W.G. 2012. *Spatio-temporal design: advances in efficient data acquisition.* John Wiley & Sons.

Mather, M., POLLARD, K. and JACOBSEN, L.A. 2009. REPORTS AMERICA. *Washington, DC: Population Reference Bureau.* pp.1-15.

Matthews, S.A., Yang, T.-C., Hayslett, K.L. and Ruback, R.B. 2010. Built environment and property crime in Seattle, 1998–2000: A Bayesian analysis. *Environment and Planning A.* **42**(6), pp.1403-1420.

McCaghy, C.H., Giordano, P.C. and Henson, T.K. 1977. Auto Theft-Offender and Offense Characteristics. *Criminology.* **15**, p367.

McCormick, A.V., Plecas, D.B. and Cohen, I.M. 2007. *Motor Vehicle Theft: An Analysis of Recovered Vehicles in the Fraser Valley.* University College of the Fraser Valley, Centre for Public Safety and Criminal Justice Research.

Messner, S.F. and Blau, J.R. 1987. Routine leisure activities and rates of crime: A macro-level analysis. *Social Forces.* **65**(4), pp.1035-1052.

Ministry of Interior. 2015. *Crime Statistics in Saudi Arabia for 1435H (In Arabic).* [Online]. [Accessed 13 February 2017]. Available from: https://www.moi.gov.sa/wps/portal/Home/sectors/moidiwan/contents/!ut/p/z0/fY49C8IwFEX_SpeM5b3E2LoWh_oFog7WLOHRBok2iW2D-PNtdnG4wzlcLhcUNKA8ve2dog2e-plvqtC4lXLDpdivFmuJVXE-lcdDzbEUcKERdqD-l-YV-xgGVYFqg4_mE6Fpg3PkuywlyTH0DH_IjEaGU6TojI8TQxesTmgSay5yjrlAviQ9P3k96-sXGFz4CQ!!/

Ministry of Interior. 2016. *Crime Statistics in Saudi Arabia for 1436H (In Arabic).* [Online]. [Accessed 13 February 2017]. Available from: https://www.moi.gov.sa/wps/portal/Home/sectors/moidiwan/contents/!ut/p/z0/fY49C8IwFEX_SpeM5b3GtHUtDvULRB2sWcKjBok2iU2D-PNtdnG4wzlcLhckdCAdvc2dovGOhpmvslK4EWJdCL5bLlYCm-p0rA_7tsCaw5kCbEH-L80r5jGOsgHZexf1J0LXe2vJ3bKUJIMfGP6QGQWGU6RotYsTQ-uNSqgTK17mWOYci4rU_OT1bC9fzERYPQ!!/p0/IZ7_11D8H2G0LO24E0AMO2THI10080=CZ6_0I44H142K83C40A6RQ7OLG1072=MECTX!QCPmoiQCAdiwanQCPmoiQCAhomeQCAcontentQCAarQCPhomeQCPnewsQCPnewsQCAarchiveQCPmoi_news_15-06-2016b_ar==/

Ministry of the Interior. 2014. *Statistical yearbook of the Ministry of Interior*. Riyadh, Saudi Arabia.

Mirrlees-Black, C., Mayhew, P. and Percy, A. 1996. *The 1996 British Crime Survey England and Wales.* London: Home Office Statistical Bulletin.

Moran, P. 1950. Notes on continuous stochastic phenomena *Biometrika* **37**, pp.17–23.

Morenoff, J.D. and Sampson, R.J. 1997. Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. *Social forces.* **76**(1), pp.31-64.

Morgan, N., Shaw, O., Feist, A. and Byron, C. 2016. *Reducing criminal opportunity: Vehicle security and vehicle crime.* Home Office.

Newman, O. 1972. *Defensible space: Crime prevention through urban design.* New York: Macmillan

NIC. 2014. *Motor Vehicle Theft Data for Riyadh.* Saudi Arabia (Unpublished): National Information Centre (NIC).

O'Rourke, N. and Hatcher, L. 2013. *A step-by-step approach to using SAS for factor analysis and structural equation modeling.* Sas Institute.

O'Sullivan, D. and Unwin, D.J. 2010. *Geographic information analysis.* Second ed. John Wiley & Sons.

Office for National Statistics. 2009. *Office for National Statistics National Population Projections 2008-based.* United Kingdom: Office for National Statistics,.

Office for National Statistics. 2012. *Crime in England and Wales, Quarterly First Release to December 2011.* United Kingdom: Office for National Statistics.

Office for National Statistics. 2013a. *Chapter 1: Property Crime - Overview.* United Kingdom: Office for National Statistics.

Office for National Statistics. 2013b. *Full report - Women in the labour market.* United Kingdom: Office for National Statistics.

Office for National Statistics. 2014. *Large increase in 20 to 34-year-olds living with parents since 1996.* [Online]. [Accessed 10 March 2016]. Available from: http://www.ons.gov.uk/ons/rel/family-demography/young-adults-living-with-parents/2013/sty-young-adults.html

Office for National Statistics. 2015a. *Annual Mid-year Population Estimates, 2014.* United Kingdom: Office for National Statistics.

Office for National Statistics. 2015b. *Overview of the UK Population.* United Kingdom: Office for National Statistics.

Office for National Statistics. 2017. *Census geography, An overview of the various geographies used in the production of statistics collected via the UK census.* [Online]. [Accessed 28 March 2017]. Available from: https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography

Paynich, R. and Hill, B. 2011. *Fundamentals of Crime Mapping: Principles and Practice.* Jones & Bartlett Learning.

Peng, C.-Y.J. and Nichols, R.N. 2003. Using multinomial logistic models to predict adolescent behavioral risk. *Journal of Modern Applied Statistical Methods.* **2**(1), p16.

Piculescu, V. 2002. *Studies on the Post-communist Transition.* Citeseer.

Piza, E., Feng, S., Kennedy, L. and Caplan, J. 2016. Place-based correlates of Motor Vehicle Theft and Recovery: Measuring spatial influence across neighbourhood context. *Urban Studies.* p0042098016664299.

Pohlman, J.T. and Leitner, D.W. 2003. A comparison of ordinary least squares and logistic regression. *Ohio Journal of Science.* **103**(5), pp.118-125.

Crime Statistics in Riyadh. 2014. [Database]. Riyadh, Saudi Arabia: Ministry of Interior, Public Security , Police Department in Riyadh.

Pringle, D.G. 1981. Causal modelling: the simon-blalock approach. In: Geo Abstracts, University of East Anglia.

Public Security. 2012. *Crimes against property.* Riyadh, Saudi Arabia: Public Security (unpublished).

Public Security. 2016. *Saudi Standards for protecting vehicles from thefts* Unpublished.

Qari, A.A., Balobaid, A.S., Rawashdeh, R.R. and Al-Sayed, M.D. 2013. The development of genetic counseling services and training program in Saudi Arabia. *Journal of genetic counseling.* **22**(6), pp.835-838.

Qhtani, A.M. and Al Fassam, A.N. 2011. Ar Riyadh Geospatial urban information system and metropolitan development strategy for Ar Riyadh. In: *ESRI international user conference,* pp.1-26.

Ratcliffe, J.H. 2005. Detecting spatial movement of intra-region crime patterns over time. *Journal of Quantitative Criminology.* **21**(1), pp.103-123.

Reher, D.S. 1998. Family ties in Western Europe: persistent contrasts. *Population and development review.* pp.203-234.

Rengert, G.F. 1997. Auto theft in central Philadelphia. *Policing for prevention: Reducing crime, public Intoxication and injury, Crime Prevention Studies.* **7**, pp.199-219.

Reno, J., Marcus, D., Robinson, L., Brennan, N. and Travis, J. 1999. Mapping crime principle and practice. *US Department of Justice.*

Rice, K.J. and Smith, W.R. 2002. Socioecological models of automotive theft: Integrating routine activity and social disorganization approaches. *Journal of Research in Crime and Delinquency.* **39**(3), pp.304-336.

Roberts, A. and Block, S. 2012. Explaining temporary and permanent motor vehicle theft rates in the United States: a crime-specific approach. *Journal of research in crime and delinquency.* p0022427812453143.

Roncek, D.W. 1981. Dangerous places: Crime and residential environment. *Social Forces.* **60**(1), pp.74-96.

Rosenshein, L., Scott, L. and Pratt, M. 2011. Finding a meaningful model. *ArcUser, Winter.*

Sa'ud, I.U.o.I.M.I. 1984. *The application of Islamic punishments and its effects on society: selections of papers presented to the Conference on Islamic Jurisprudence organized by the Islamic University of Imam Muhammad Ibn Sa'ud, Riyadh 1396 H.* Imam University Press.

Sadik-Khan, J. 2012. New York City bridge traffic volumes 2010. *New York, NY: New York City Department of Transportation.*

Sallybanks, J. and Brown, R. 1999. *Vehicle crime reduction: turning the corner.* Home Office, Policing and Reducing Crime Unit, Research, Development and Statistics Directorate.

Saville, G. and Murdie, R. 1988. The spatial analysis of motor vehicle theft: A case study of Peel Region, Ontario. *Journal of Police Science and Administration.* **16**(2), pp.126-135.

Sawada, M. 2001. Global Spatial Autocorrelation indices–Moran's I, Geary's C and the General Cross-Product Statistic. *Laboratory of Paleoclimatology and Climatology, Dept. Geography, University of Ottawa,(Mimeo).*

Scott, L. and Pratt, M. 2009. *Answering why questions: An introduction to using regression analysis with spatial data*. ArcUser.

Serajzadeh, S.H. 2001. Islam and crime: the moral community of muslims. *Journal of Arabic and Islamic Studies.* **4**(1), pp.111-131.

Shaw, C.R., Cottrell, L.S., MACKAY, H.D. and Zorbaugh, F.M. 1929. *Delinquency Areas. A study of the geographical distribution of school truants, juvenile delinquents, and adult offenders in Chicago.[By] CR Shaw... With the collaboration of Frederick M. Zorbaugh, Henry D. McKay... Leonard S. Cottrell.* University Press.

Shaw, C.R. and McKay, H.D. 1942. *Juvenile delinquency and urban areas: A study of rates of delinquents in relation to differential characteristics of local communities in American cities.* University of Chicago Press Chicago.

Sherman, L.W., Gartin, P.R. and Buerger, M.E. 1989. Hot spots of predatory crime: routine activities and the criminology of place*. *Criminology*. **27**(1), pp.27-56.

Sherman, L.W. and Weisburd, D. 1995. General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial. *Justice Quarterly*. **12**(4), pp.625-648.

Silver, W. 2007. *Crime statistics in Canada, 2006.* Canadian Centre for Justice Statistics.

Souryal, S.S. 1988. The role of Shariah law in deterring criminality in Saudi-Arabia. *International Journal of Comparative and Applied Criminal Justice.* **12**(1-2), pp.1-25.

Spelman, W. 1995. Criminal careers of public places. *Crime and place: Crime prevention studies.* **4**, pp.115-142.

Starkweather, J. and Moske, A.K. 2011. *Multinomial logistic regression.* [Online]. [Accessed 1 May 2017]. Available from: https://it.unt.edu/sites/default/files/mlr_jds_aug2011.pdff

Statistics Canada. 2017. *Census Profile. 2016 Census.* [Online]. [Accessed 4 May 2017]. Available from: http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/page.cfm?Lang=E&Geo1=PR&Code1=01&Geo2=PR&Code2=01&Data=Count&SearchText=Canada&SearchType=Begins&SearchPR=01&TABID=1&B1=All

Stipak, B. 1988. Alternatives to population-based crime rates. *International Journal of Comparative and Applied Criminal Justice.* **12**(1-2), pp.247-260.

Suresh, G. and Tewksbury, R. 2013. Locations of motor vehicle theft and recovery. *American Journal of Criminal Justice.* **38**(2), pp.200-215.

Swan, J. 2012. 2011 Census: Population Estimates for the United Kingdom, 27 March 2011.

Tabachnick, B.G., Fidell, L.S. and Osterlind, S.J. 2001. Using multivariate statistics.

The World Bank. 2016. *Labor force, female, 2011*. [Online]. [Accessed 15 March 2016]. Available from: http://data.worldbank.org/indicator/SL.TLF.TOTL.FE.ZS

Tobler, W.R. 1970. A computer movie simulating urban growth in the Detroit region. *Economic geography*. **46**, pp.234-240.

Tonry, M. 2011. *The Oxford handbook of crime and public policy.* Oxford University Press.

Tremblay, P., Clermont, Y. and Cusson, M. 1994. JOCKEYS AND JOYRIDERS Changing Patterns in Car Theft Opportunity Structures. *British Journal of Criminology*. **34**(3), pp.307-321.

Tu, Y.-K., Kellett, M., Clerehugh, V. and Gilthorpe, M.S. 2005. Problems of correlations between explanatory variables in multiple regression analyses in the dental literature. *British dental journal.* **199**(7), pp.457-461.

U.S. Department of Justice. 2000. Analysis of motor vehicle theft using survival model. *Crime in the United States – 2000.* . [Online]. Available from: https://ucr.fbi.gov/crime-in-the-u.s/2000/00sec5.pdf

U.S.Bureau of Labor Statistics. 2013. *Women in the Labor Force: A Databook.* United States.

United States Census Bureau. 2015. *Population and Housing Unit Estimates.* [Online]. [Accessed 15 March 2016]. Available from: http://www.census.gov/popest/data/national/totals/2014/index.html

Valiela, I. 2009. *Doing science: design, analysis, and communication of scientific research.* Oxford University Press.

Van Dijk, J., Tseloni, A. and Farrell, G. 2012. *The international crime drop: new directions in research.* Springer.

Van Koppen, P.J. and Jansen, R.W. 1999. The time to rob: variations in time of number of commercial robberies. *Journal of Research in Crime and Delinquency.* **36**(1), pp.7-29.

Vito, G.F. and Maahs, J.R. 2015. *Criminology.* Jones & Bartlett Publishers.

Wallace, M. 2003. *Motor vehicle theft in Canada, 2001.* Canada: Canadian Centre for Justice Statistics.

Wallace, M., Wisener, M. and Collins, K. 2006. *Neighbourhood characteristics and the distribution of crime in Regina.* Statistics Canada.

Walsh, J.A. and Taylor, R.B. 2007a. Community structural predictors of spatially aggregated motor vehicle theft rates: Do they replicate? *Journal of Criminal Justice.* **35**(3), pp.297-311.

Walsh, J.A. and Taylor, R.B. 2007b. Predicting decade-long changes in community motor vehicle theft rates impacts of structure and surround. *Journal of Research in Crime and Delinquency.* **44**(1), pp.64-90.

Wang, C.L., Ketchen, D.J. and Bergh, D.D. 2012. *West Meets East: Toward Methodological Exchange.* Emerald Group Publishing.

Webb, B. 1994. Steering column locks and motor vehicle theft: Evaluations from three countries. *Crime prevention studies.* **2**, pp.71-89.

Weeks, J.R. 2004. The role of spatial analysis in demographic research. *Spatially integrated social science.* pp.381-399.

Weisburd, D., Groff, E. and Yang, S.-M. 2011. Understanding developmental crime trajectories at places: social disorganization and opportunity perspectives at micro units of geography. *National Institute of Justice, Washington, DC.*

Weisel, D.L., Smith, W.R., Garson, G.D., Pavlichev, A. and Wartell, J. 2006. Motor vehicle theft: Crime and spatial analysis in a non-urban region. *Rockville, MD: National Institute of Justice.*

Wheeler, D. and Tiefelsdorf, M. 2005. Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems.* **7**(2), pp.161-187.

White, E. 2012. *2011 Census: Key Statistics for England and Wales, March 2011.* United Kingdom: Office for National Statistics.

White, M.D. 2007. *Current issues and controversies in policing.* Pearson Allyn and Bacon.

Whitehead, J.T. 2012. *Juvenile justice: An introduction.* Elsevier.

Willits, D., Broidy, L., Gonzales, A. and Denman, K. 2011. *Place and neighborhood crime: Examining the relationship between schools, churches, and alcohol related establishments and crime.* Institute for Social Research.

Wong, D.W. 2009. Modifiable Areal Unit Problem. *International Encyclopedia of Human Geography.* pp.169-174.

Wortley, R. and Mazerolle, L. 2008. Environmental criminology and crime analysis: situating the theory, analytic approach and application. In: Wortley, R. and Mazerolle, L. eds. *Environmental criminology and crime analysis.* Devon: Willan, pp.1-18.

Wuensch, K.L. 2012. Principal Components Analysis - SPSS. [Online]. [Accessed 10 April 2017]. Available from: https://www.google.co.uk/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwiC49nTj7rTAhXJlxoKHazPBw0QFggjMAA&url=http%3A%2F%2Fcore.ecu.edu%2Fpsyc%2Fwuenschk%2FMV%2FFA%2FPCA-SPSS.docx&usg=AFQjCNH-ov3ixyPRT6sKfGHJafksEkeXlQ&sig2=oTtLIOnbsDhEaSHzNIbbng

Yaremko, R., Harari, H., Harrison, R.C. and Lynn, E. 2013. *Handbook of research and quantitative methods in psychology: For students and professionals.* Psychology Press.

Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q.P. and Lillard Jr, J.W. 2014. A study of effects of multicollinearity in the multivariable analysis. *International journal of applied science and technology.* **4**(5), p9.

Young, R. and Garland, D. 2002. *The Culture of Control: Crime and Social Order in Contemporary Society*. JSTOR.

Appendix A

Output from the OLS Regression Models

The following tables and graphs present the output from the OLS regression models that were described in Chapter 5 and shown in Chapter 7. They were implemented in this study to model MVT during the four time periods of the day using routine activity theory (RAT), crime pattern theory (CPT) and the integration of the theories. The graphs and tables presented in this appendix provide more details about how the OLS regression models have met the main OLS assumptions, as follows.

1. Assumption of the low degree of collinearity

As can be seen from the collinearity statistics in the tables below for each variable, the tolerance was greater than 0.1 and the VIF <10. Consequently, there was no serious collinearity between the independent variables.

2. Assumption of the linearity

The partial regression plots in the figures are used to show the correlation between the MVT rates and each independent variable after the influence of other variables have been removed. From the graphs below, it can be seen that there are linear relationships between the dependent and independent variables.

3. Assumption of homoscedasticity of the model

It can be seen from the scatter plots in the figures below that there was almost homoscedasticity for each model, since the variance of the residuals was approximately equal across the predicted values so the assumption of homoscedasticity of the model was met.

4. Assumption that the residuals are normally distributed

By looking at the Normal p-p plots of Regression Standardized Residual below for each model. It is clear that the assumption was not violated and the residuals were distributed close to the line of expected values.

The following sections will present the tables and graphs for every model to show how the above assumptions of the OLS regression models were met.

A.1 MVT and RAT

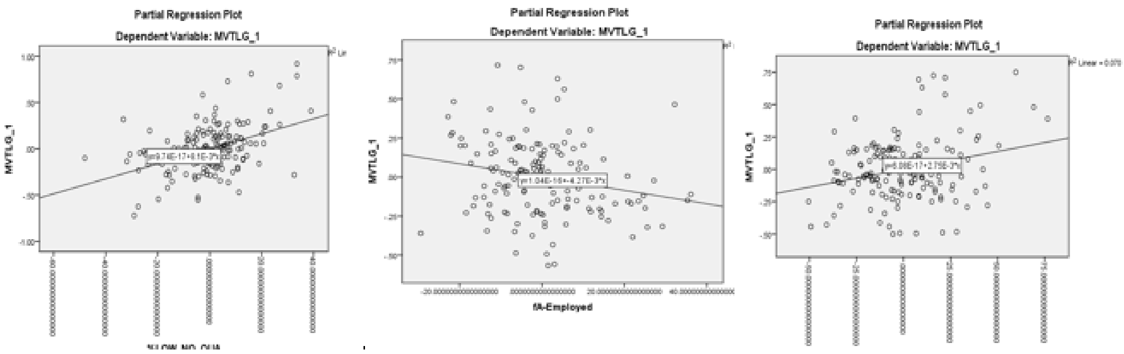
A.1.1 The Original Variables associated with RAT

A.1.1.1 MVT rates during Period One

Table 1. Estimated coefficients for variables in the OLS regression models during Period One

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Non-SA males	0.231	0.001	0.001	0.748	1.337
Employed Females	-0.188	0.007	0.002	0.730	1.371
LNEQ	0.422	0.000	0.001	0.676	1.478
Adjusted R^2	0.45				
Durbin-Watson statistic	1.74				
Std. Error of the Estimate	0.23529				

Assumption of the linearity:



A. LNEQ B. Employed females C. Non-SA males

Figure 1. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

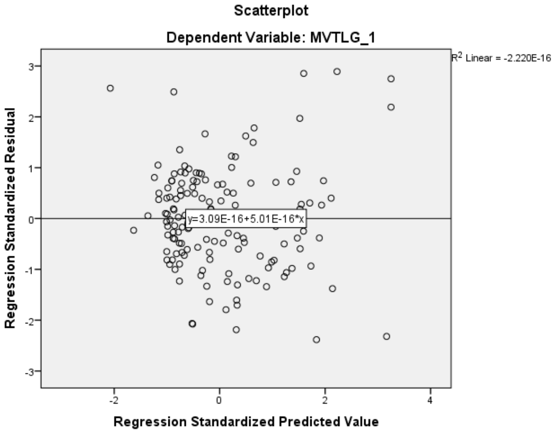


Figure 2. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

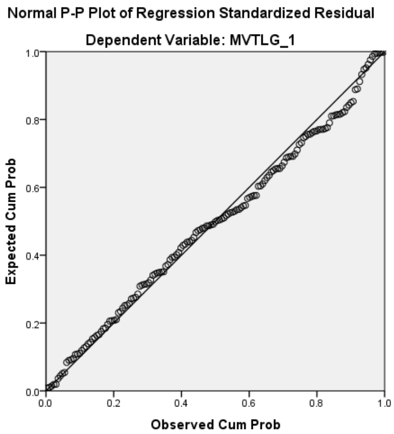


Figure 3. Regression Standardized Residual for dependent variable

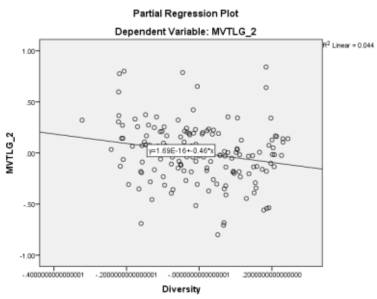
A.1.1.2 MVT rates during Period Two

Table 3. Estimated coefficients for variables in the OLS regression models during Period Two

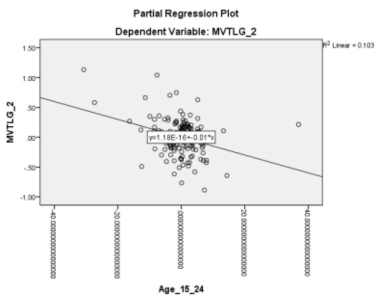
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Age 15-24	-0.299	0.004	0.004	0.516	1.9
Non-SA males	0.343	0.000	0.001	0.688	1.45
Employed FE	-0.38	0.000	0.002	0.727	1.37

Single	0.248	0.008	0.003	0.597	1.67
Diversity	-0.152	0.010	0.176	0.793	1.26
Adjusted R^2	0.59				
Durbin-Watson statistic	1.71				
Std. Error of the Estimate	0.284				

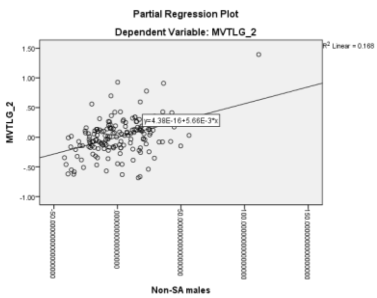
Assumption of the linearity



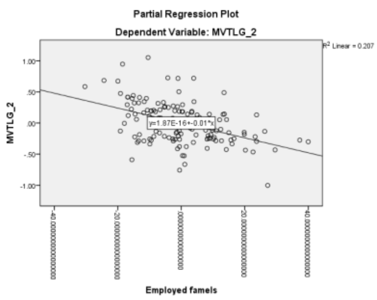
A. Diversity



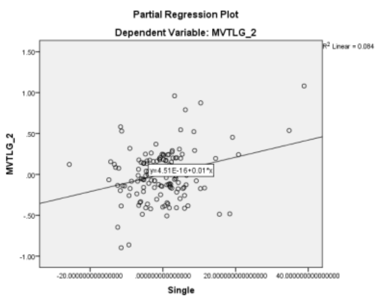
B. Age 15-24



C. Non-SA males



D. Employed females



E. Single

Figure 4. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

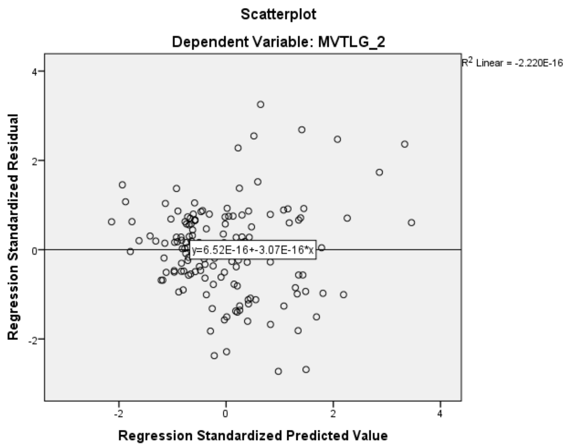


Figure 5. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

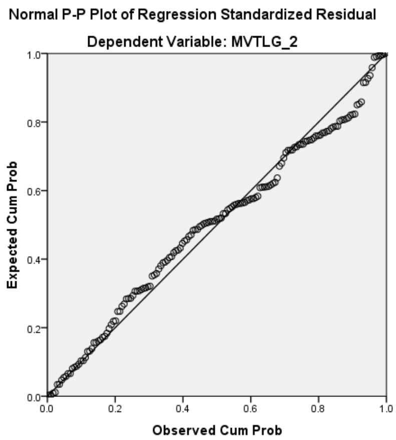


Figure 6. Regression Standardized Residual for dependent variable

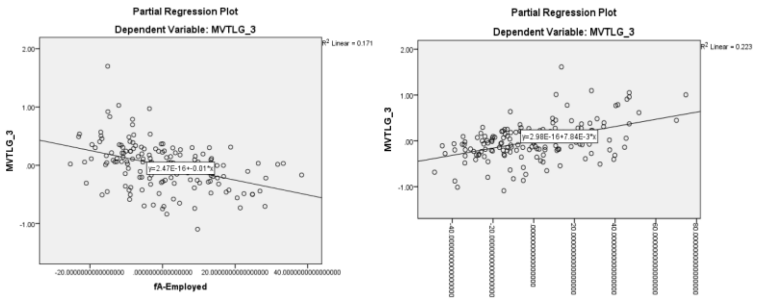
A.1.1.3 MVT rates during period Three

Table 3. Estimated coefficients for variables in the OLS regression models during Period Three

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Non-SA males	0.43	0.00	0.001	0.84	1.18
Employed FE	-0.36	0.00	0.001	0.84	1.18
Adjusted R^2	0.44				

Durbin-Watson statistic	1.75
Std. Error of the Estimate	0.363

Assumption of the linearity:



A. Employed females B. Non-SA males

Figure 7. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

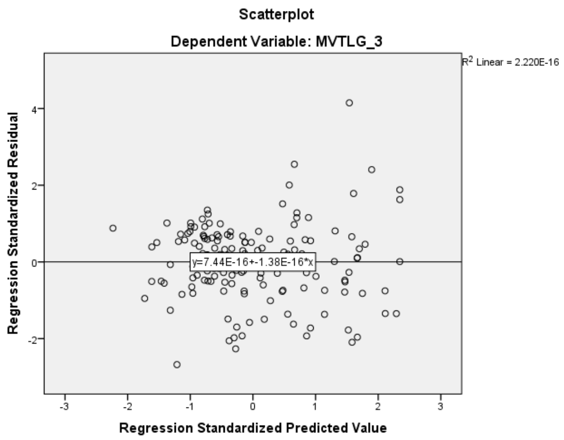


Figure 8. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed

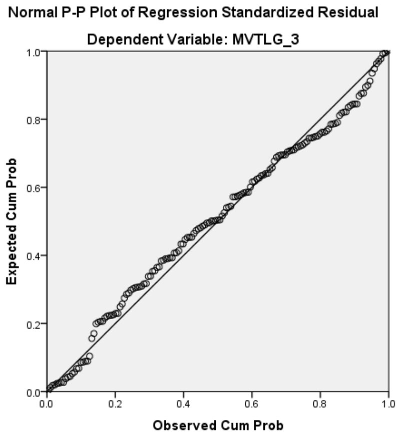


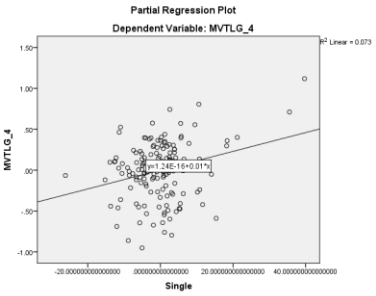
Figure 9. Regression Standardized Residual for dependent variable

A.1.1.4 MVT rates during Period Four

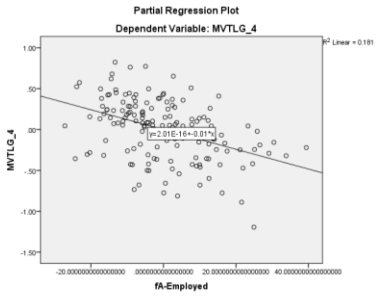
Table 4. Estimated coefficients for variables in the OLS regression models during Period four

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Age 15-24	-0.22	0.003	0.004	0.519	1.92
Non-SA males	0.446	0.000	0.001	0.701	1.426
Employed FA	-0.34	0.000	0.002	0.836	1.197
Single	0.246	0.001	0.003	0.598	1.671
Adjusted R^2	0.53				
Durbin-Watson statistic	1.587				
Std. Error of the Estimate	0.334				

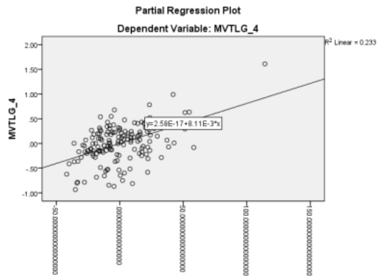
Assumption of the linearity:



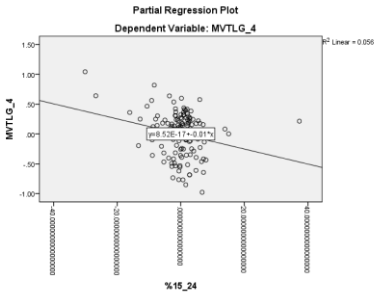
A. Single



B. Employed females



C. Non-SA males



C. Age 15-24

Figure 10. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

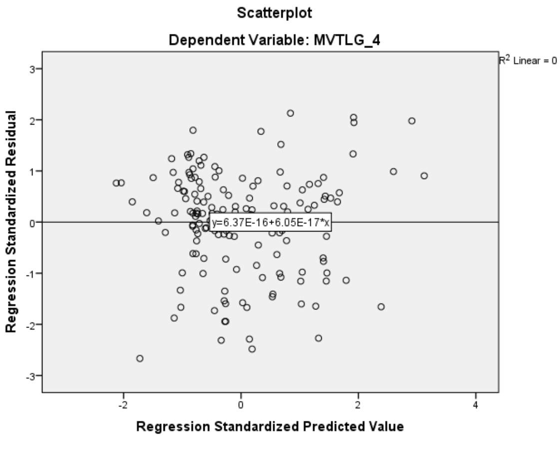


Figure 11. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

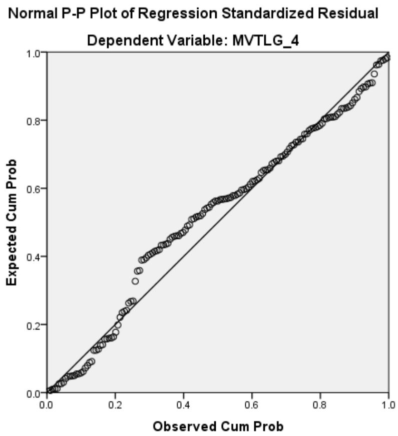


Figure 12. Regression Standardized Residual for dependent variable

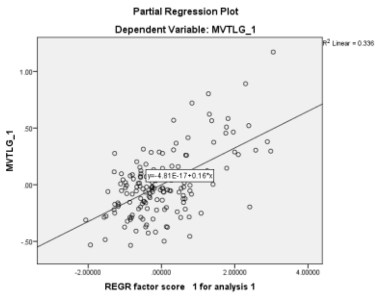
A.1.2 The PCA Scores associated with RAT

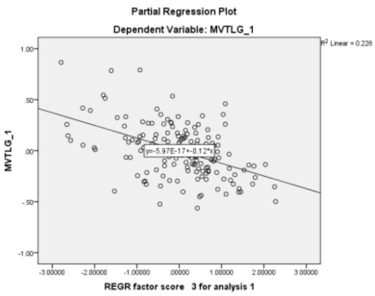
A.1.2.1 MVT rates during Period One

Table 5. Estimated coefficients for PC scores in the OLS regression models during Period One

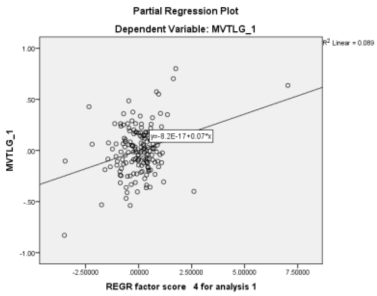
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.50	0.000	0.018	1.00	1.00
PC3	-0.38	0.000	0.018	1.00	1.00
PC4	0.223	0.000	0.018	1.00	1.00
PC5	0.18	0.002	0.018	1.00	1.00
Adjusted R2	0.47				
Durbin-Watson statistic	1.72				
Std. Error of the Estimate	0.2309				

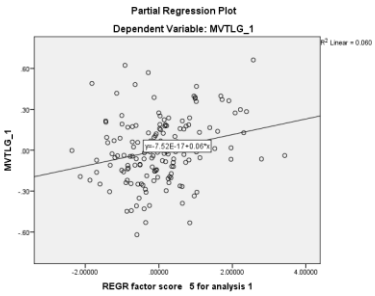
Assumption of the linearity:





A. PC1 B. PC3





C. PC4 D. PC5

Figure 13. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

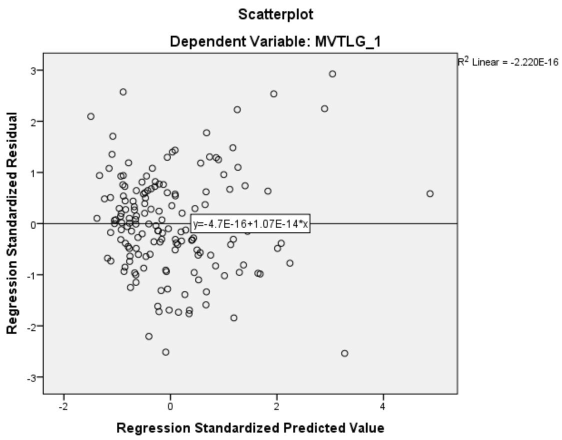


Figure 14. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

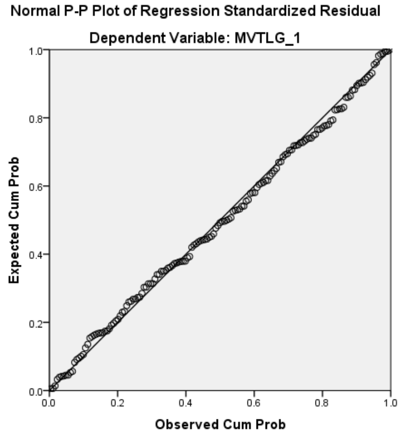


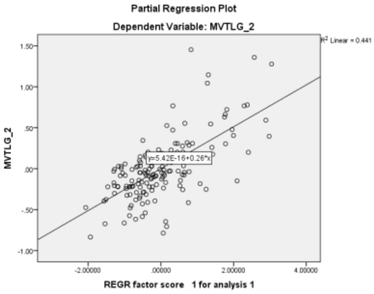
Figure 15. Regression Standardized Residual for dependent variable

A.1.2.2 MVT rates during Period Two

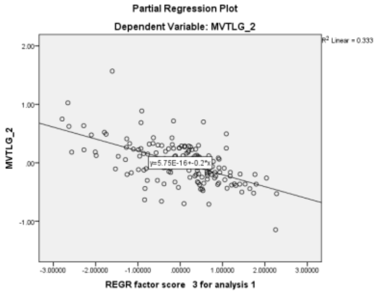
Table 6. Estimated coefficients for PC Scores in the OLS regression models during Period Two

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.57	0.000	0.023	1.00	1.00
PC3	-0.46	0.000	0.023	1.00	1.00
PC5	0.10	0.046	0.023	1.00	1.00
PC6	-0.13	0.014	0.023	1.00	1.00
Adjusted R2	0.56				
Durbin-Watson statistic	1.70				
Std. Error of the Estimate	0.2918				

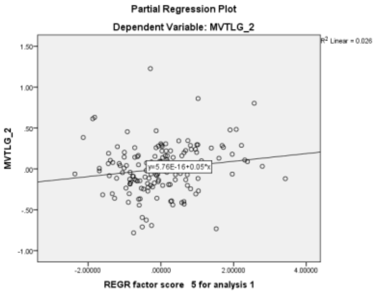
Assumption of the linearity:



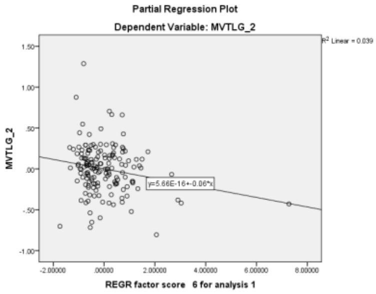
A. PC1



B. PC3



C. PC5



D. PC6

Figure 16. Partial correlation plots between and the independent variables and MVT rates

Assumption of homoscedasticity of the model:

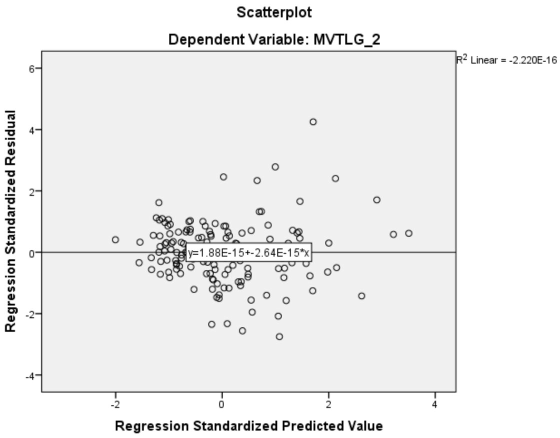


Figure 17. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

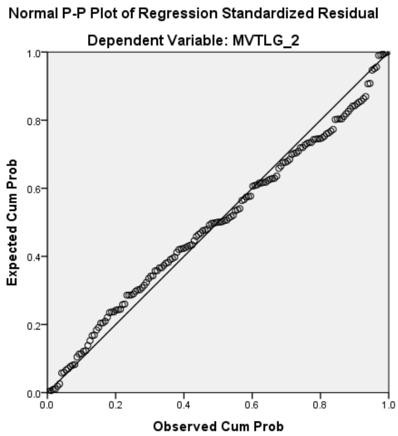


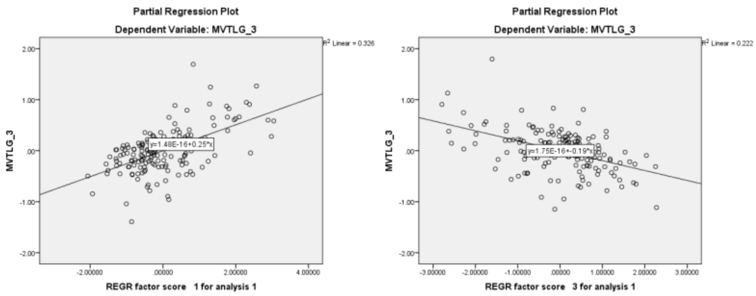
Figure 18. Regression Standardized Residual for dependent variable

A.1.2.3 MVT rates during Period Three

Table 7. Estimated coefficients for PC Scores in the OLS regression models during Period Three

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.52	0.000	0.029	1.00	1.00
PC3	-0.40	0.000	0.029	1.00	1.00
Adjusted R2	0.42				
Durbin-Watson statistic	1.64				
Std. Error of the Estimate	0.36733				

Assumption of the linearity:



A. PC1 B. PC3

Figure 19. Partial correlation plots between and the independent variables and MVT rates

Assumption of homoscedasticity of the model:

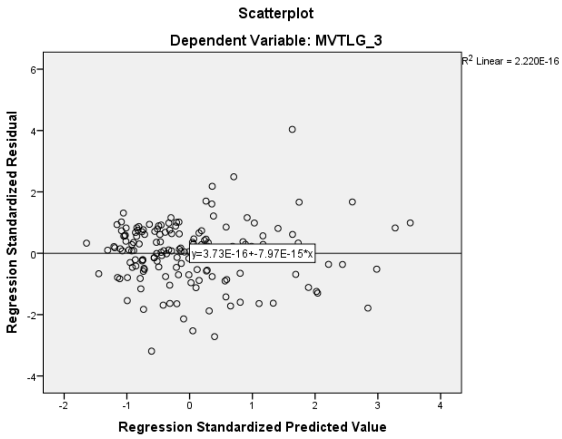


Figure 20. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

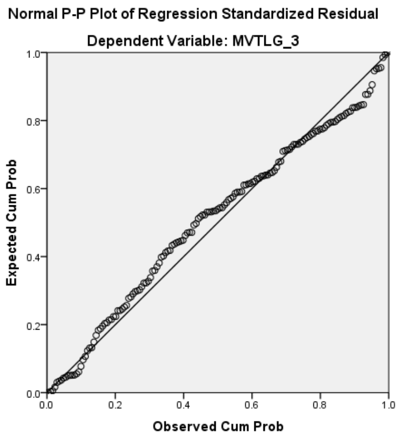


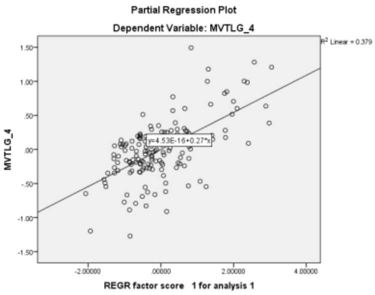
Figure 21. Regression Standardized Residual for dependent variable

A.1.2.4 MVT rates during Period Four

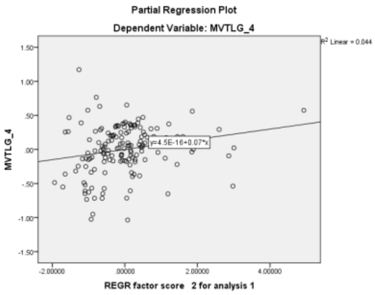
Table 8. Estimated coefficients for PC Scores in the OLS regression models during Period Four

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.55	0.000	0.028	1.00	1.00
PC2	0.15	0.009	0.028	1.00	1.00
PC3	-0.39	0.000	0.028	1.00	1.00
Adjusted R2	0.48				
Durbin-Watson statistic	1.529				
Std. Error of the Estimate	0.3516				

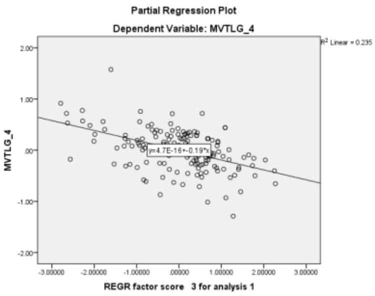
Assumption of the linearity:



A. PC1



B. PC2



C. PC3

Figure 22. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

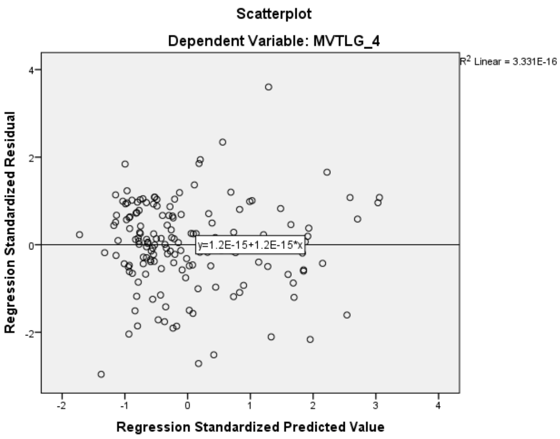


Figure 23. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

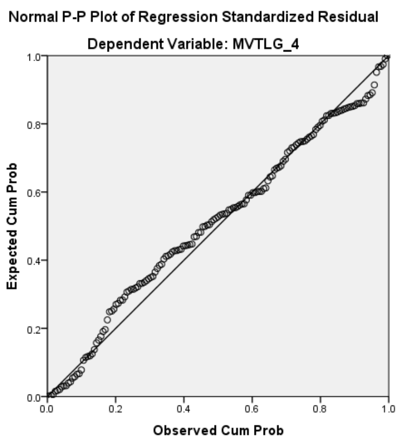


Figure 24. Regression Standardized Residual for dependent variable

A.2 MVT and CPT

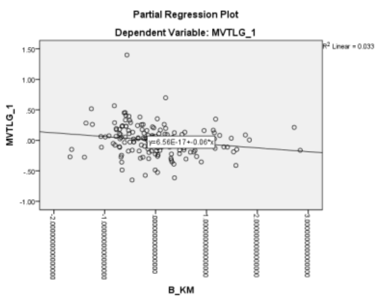
A.2.1 The Original Variables

A.2.1.1 MVT rates during Period One

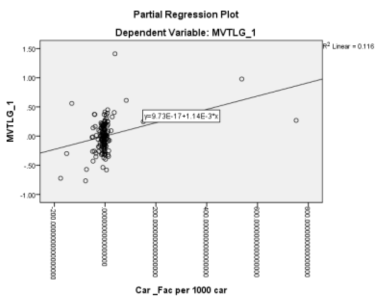
Table 9. Coefficients for the CPT variables in OLS regression models during Period One

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Car Facilities	0.324	0.000	0.000	0.787	1.27
Apartments	0.422	0.000	0.001	0.788	1.26
Car Parks	0.240	0.001	0.004	0.780	1.28
Roads B	-0.166	0.023	0.027	0.783	1.27
Adjusted R2	0.35				
Durbin-Watson statistic	1.476				
Std. Error of the Estimate	0.2558				

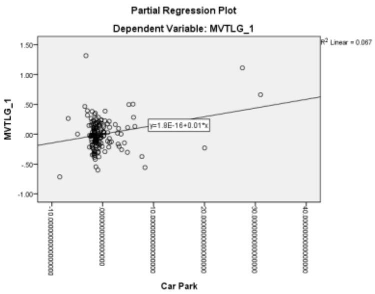
Assumption of the linearity:

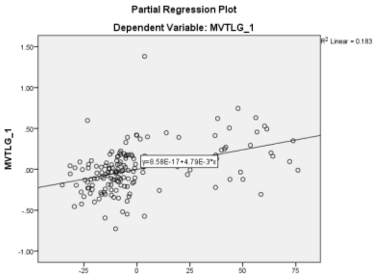


A. Roads-B



B. Car facilities





C. Car park D. Apartments

Figure 25. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

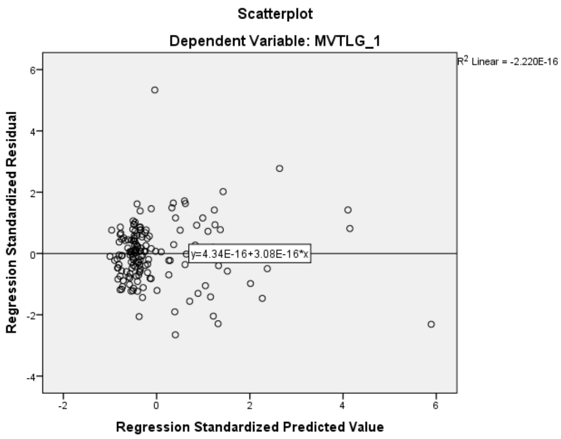


Figure 26. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

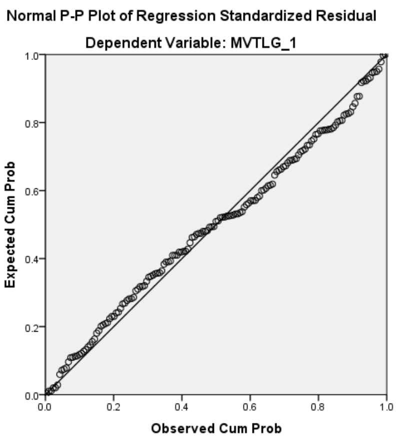


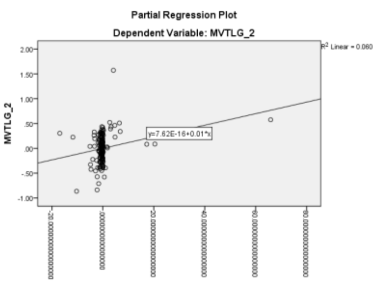
Figure 27. Regression Standardized Residual for dependent variable

A.2.1.2 MVT rates during Period Two

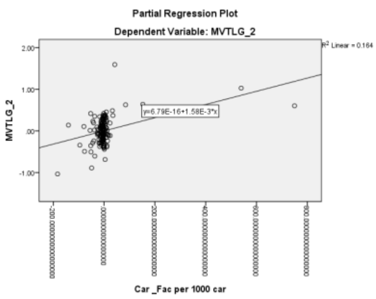
Table 10. Coefficients for the CPT variables in OLS regression models during Period Two

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Car Facilities	0.324	0.000	0.000	0.783	1.277
Apartments	0.45	0.000	0.001	0.992	1.008
Car Parks	0.32	0.000	0.005	0.702	1.425
Industrial use	0.174	0.002	0.004	0.877	1.141
Adjusted R2	0.57				
Durbin-Watson statistic	1.313				
Std. Error of the Estimate	0.29003				

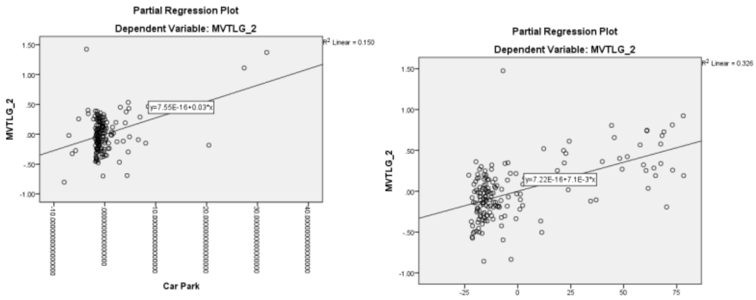
Assumption of the linearity:



A. Industrial areas



B. Car facilities



C. Car park D. Apartments

Figure 28. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

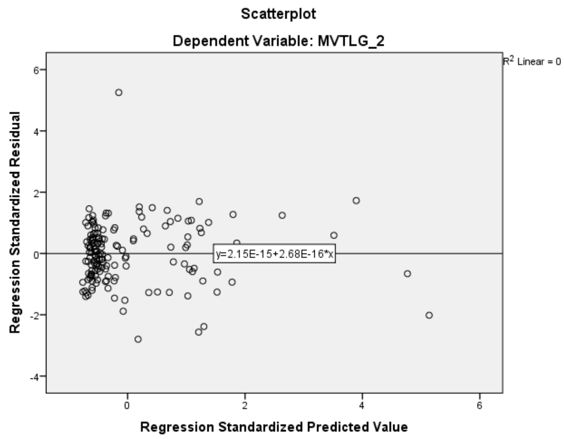


Figure 29. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

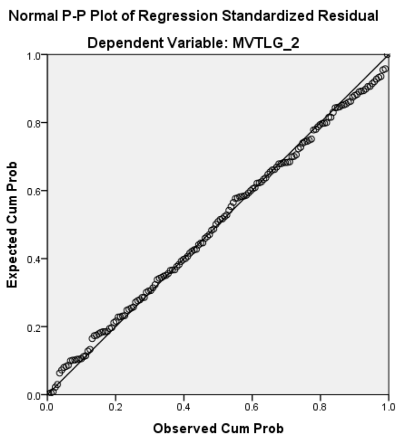


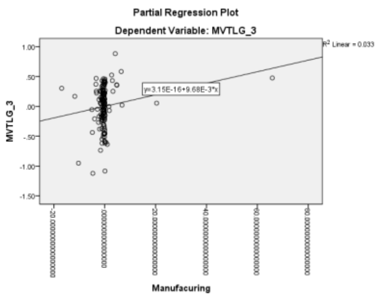
Figure 30. Regression Standardized Residual for dependent variable

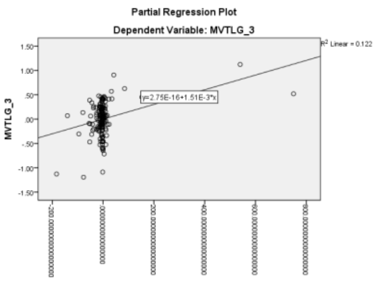
A.2.1.3 MVT rates during Period Three

Table 11. Coefficients for the CPT variables in OLS regression models during Period Three

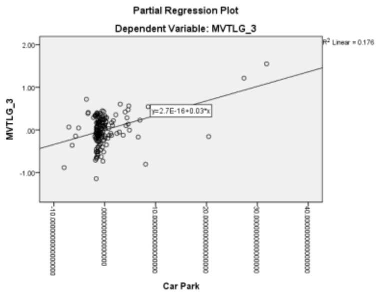
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Car Facilities	0.281	0.000	0.000	0.783	1.277
Apartments	0.442	0.000	0.001	0.992	1.008
Car Parks	0.36	0.000	0.006	0.702	1.425
Industrial use	0.132	0.024	0.004	0.877	1.141
Adjusted R2	0.54				
Durbin-Watson statistic	1.45				
Std. Error of the Estimate	0.3285				

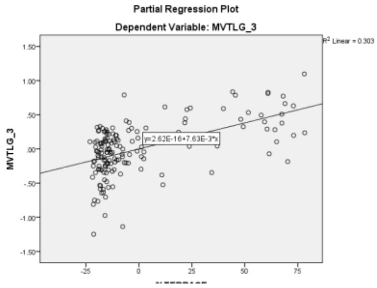
Assumption of the linearity:





A. Industrial use B. Car facilities





C. Car park D. Apartments

Figure 31. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

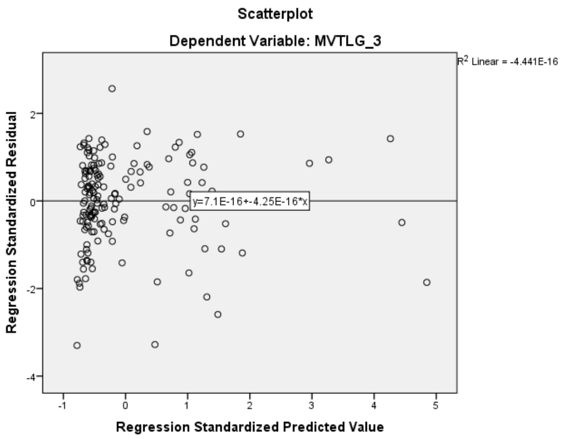


Figure 32. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed

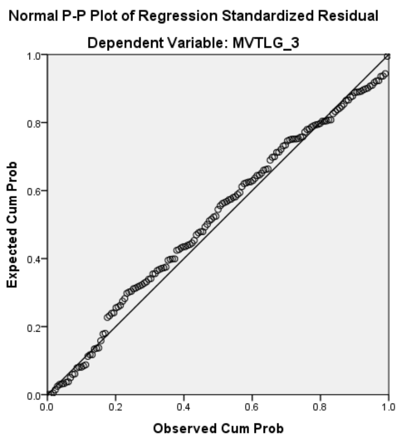


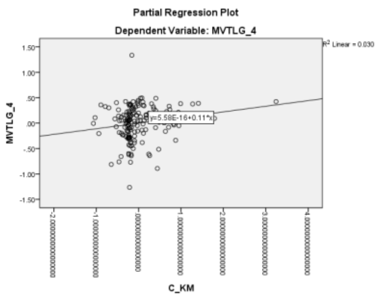
Figure 33. Regression Standardized Residual for dependent variable

A.2.1.4 MVT rates during Period Four

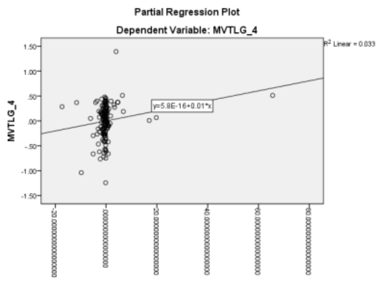
Table 12. Coefficients for the CPT variables in OLS regression models during Period Four

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
Car Facilities	0.284	0.000	0.000	0.781	1.280
Apartments	0.42	0.000	0.001	0.814	1.231
Car Parks	0.29	0.000	0.006	0.696	1.437
Industrial use	0.137	0.024	0.004	0.870	1.150
Roads C	0.133	0.034	0.052	0.810	1.235
Adjusted R2	0.51				
Durbin-Watson statistic	1.336				
Std. Error of the Estimate	0.33954				

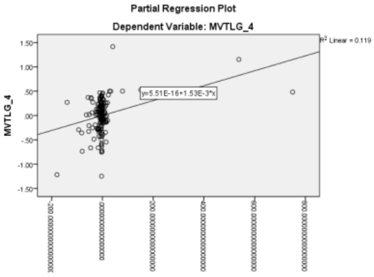
Assumption of the linearity:

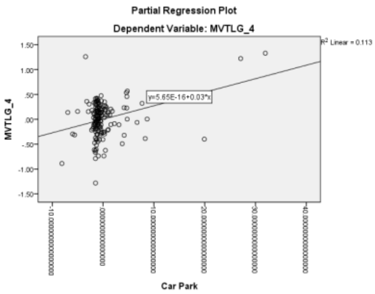


A. Roads-C

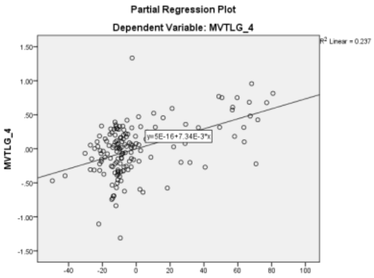


B. Industrial use





C. Car facilities D. Car parks



E. Apartments

Figure 34. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

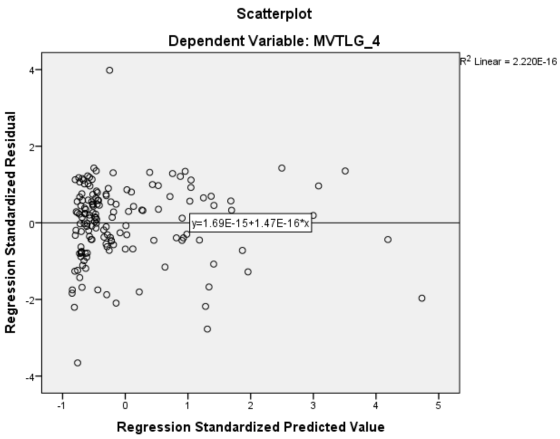


Figure 35. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed

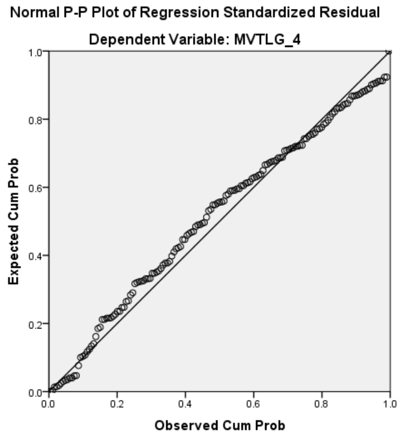


Figure 36. Regression Standardized Residual for dependent variable

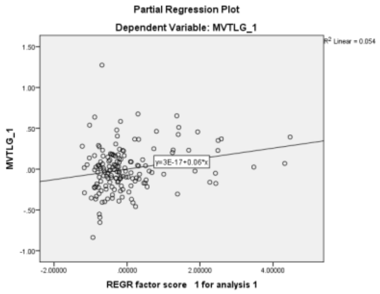
A.2.2 The PCA Scores associated with CPT

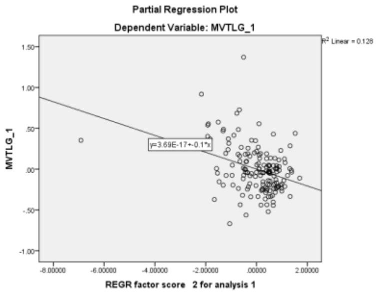
A.2.2.1 MVT rates during Period One

Table 13. Estimated coefficients for PC scores in OLS regression models during Period One

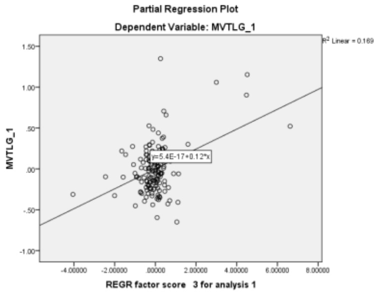
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.20	0.004	0.022	1.00	1.00
PC2	-0.32	0.000	0.022	1.00	1.00
PC3	0.38	0.000	0.022	1.00	1.00
Adjusted R^2	0.27				
Durbin-Watson statistic	1.217				
Std. Error of the Estimate	0.27196				

Assumption of the linearity:





A. PC1 B. PC2



C. PC3

Figure 37. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

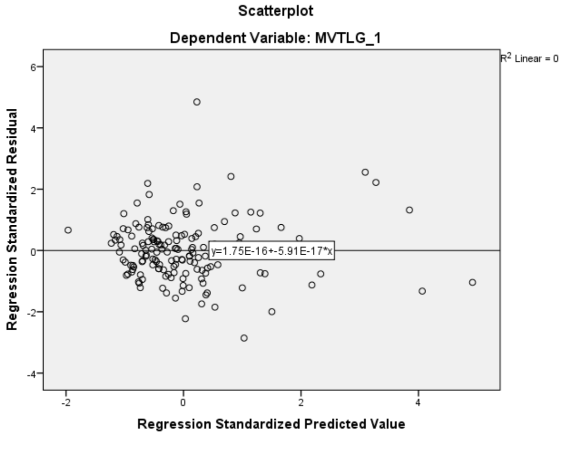


Figure 38. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

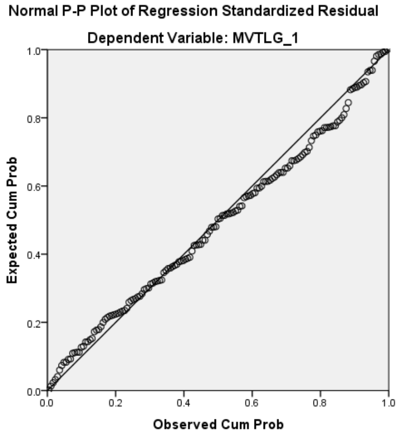


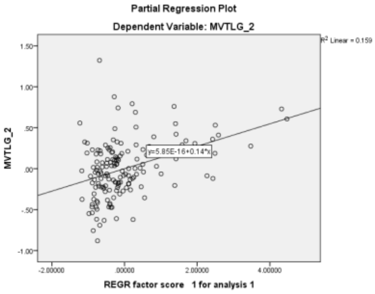
Figure 39. Regression Standardized Residual for dependent variable

A.2.2.2 MVT rates during Period Two

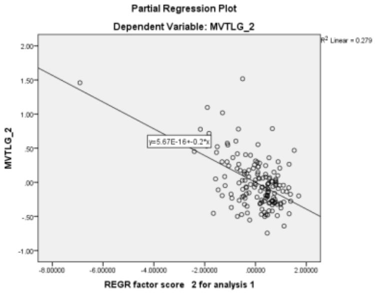
Table 14. Estimated coefficients for PC scores in OLS regression models during Period Two

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.31	0.000	0.025	1.00	1.00
PC2	-0.44	0.000	0.025	1.00	1.00
PC3	0.44	0.000	0.025	1.00	1.00
Adjusted R^2	0.48				
Durbin-Watson statistic	1.365				
Std. Error of the Estimate	0.31827				

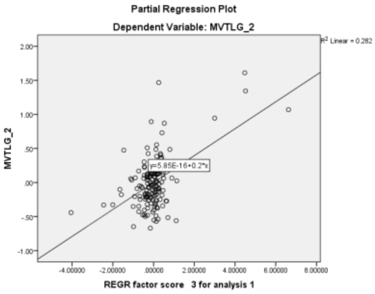
Assumption of the linearity:



A. PC1



B. PC2



C. PC3

Figure 40. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

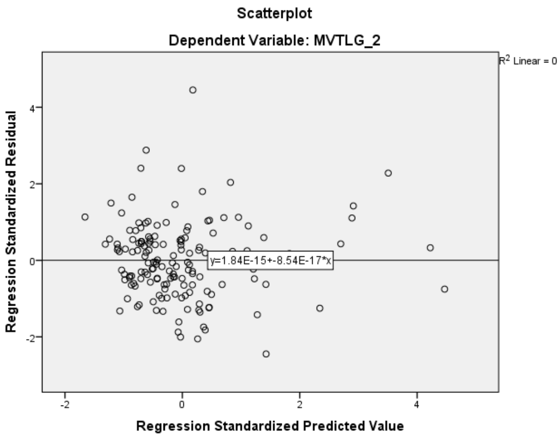


Figure 41. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

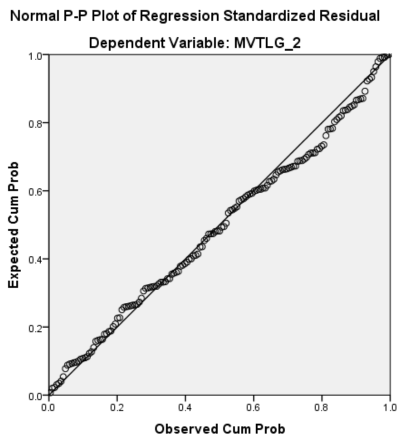


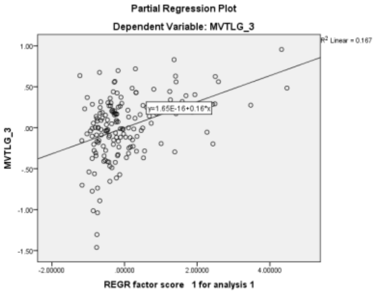
Figure 42. Regression Standardized Residual for dependent variable

A.2.2.3 MVT rates during Period Three

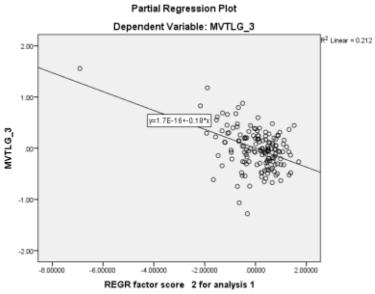
Table 15. Estimated coefficients for PC scores in OLS regression models during Period Three

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.32	0.000	0.029	1.00	1.00
PC2	-0.38	0.000	0.029	1.00	1.00
PC3	0.43	0.000	0.029	1.00	1.00
PC4	0.142	0.018	0.029	1.00	1.00
Adjusted R^2	0.45				
Durbin-Watson statistic	1.34				
Std. Error of the Estimate	0.36003				

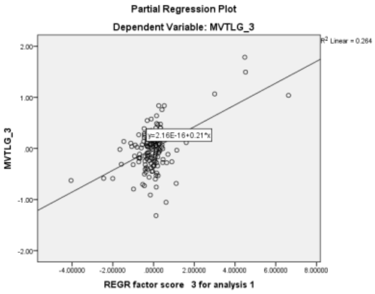
Assumption of the linearity:



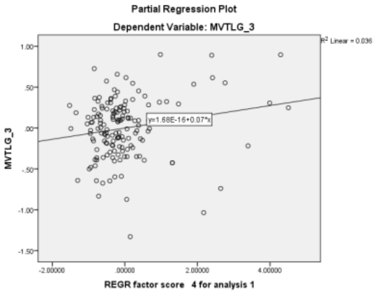
A. PC1



B. PC2



C. PC3



D. PC4

Figure 43. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

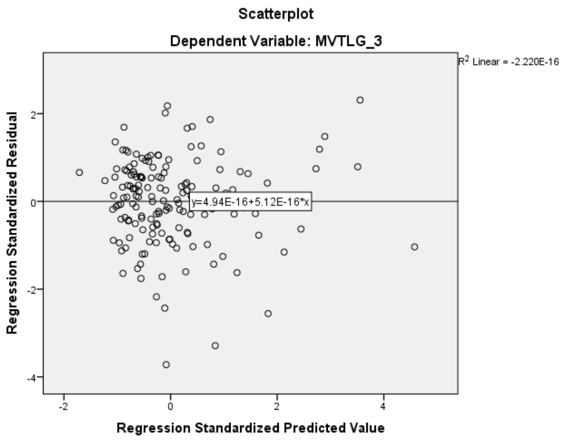


Figure 44. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

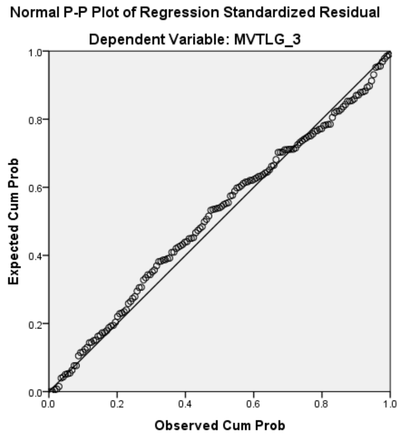


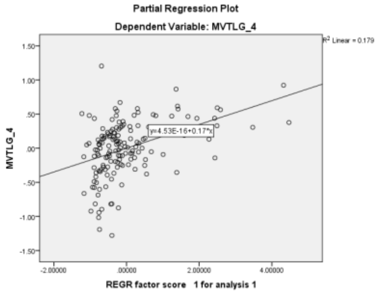
Figure 45. Regression Standardized Residual for dependent variable

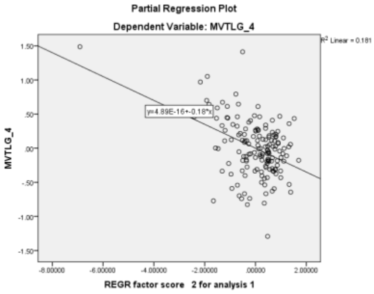
A.2.2.4 MVT rates during Period Four

Table 16. Estimated coefficients for PC scores in OLS regression models during Period Four.

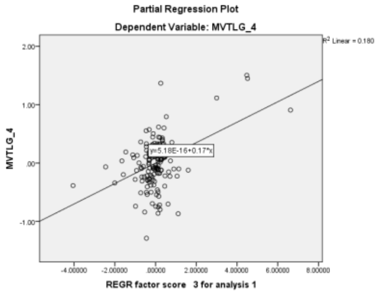
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.35	0.000	0.030	1.00	1.00
PC2	-0.35	0.000	0.030	1.00	1.00
PC3	0.35	0.000	0.030	1.00	1.00
PC4	0.179	0.004	0.030	1.00	1.00
Adjusted R^2	0.40				
Durbin-Watson statistic	1.32				
Std. Error of the Estimate	0.377				

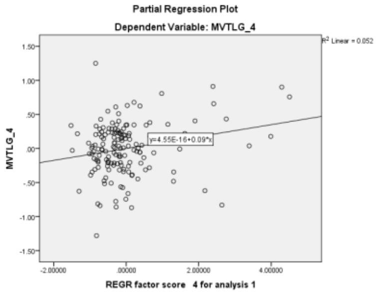
Assumption of the linearity:





A. PC1 B. PC2





C. PC3 D. PC4

Figure 46. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

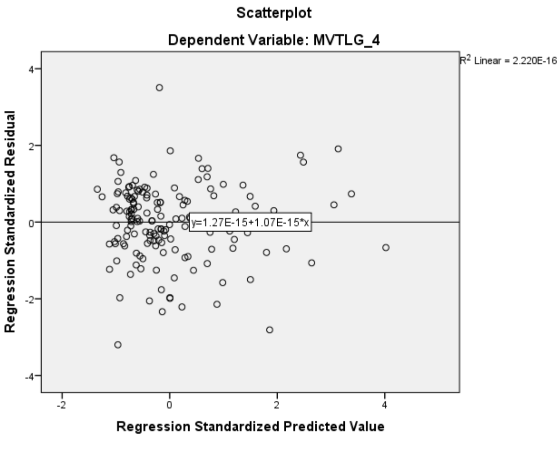


Figure 47. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

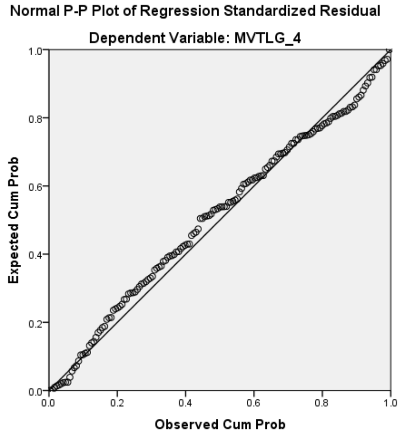


Figure 48. Regression Standardized Residual for dependent variable

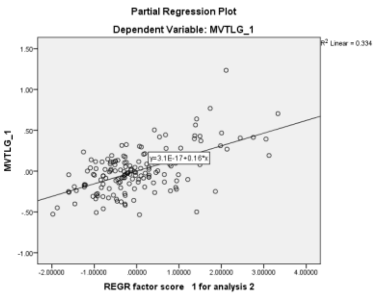
A.3 Integration of the RAT and CPT Models

A.3.1 MVT rates during Period One

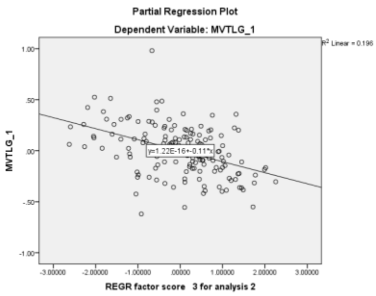
Table 17. Estimated coefficients for PC scores for integrated theories in OLS regression models during Period One

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.485	0.000	0.018	1.00	1.00
PC3	-0.338	0.000	0.018	1.00	1.00
PC4	0.367	0.000	0.018	1.00	1.00
PC5	0.179	0.002	0.018	1.00	1.00
PC8	-0.114	0.044	0.018	1.00	1.00
Adjusted R^2	0.51				
Durbin-Watson statistic	1.75				
Std. Error of the Estimate	0.22266				

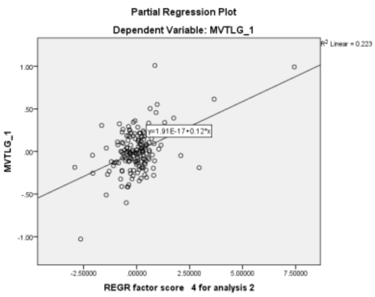
Assumption of the linearity:



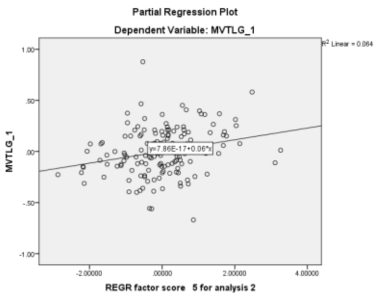
A. PC1



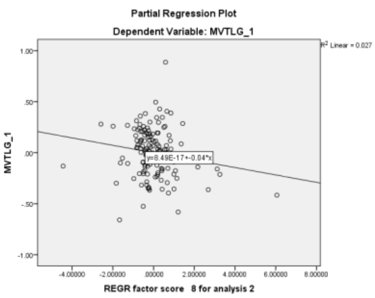
B. PC3



C. PC4



D. PC5



E. PC6

Figure 49. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

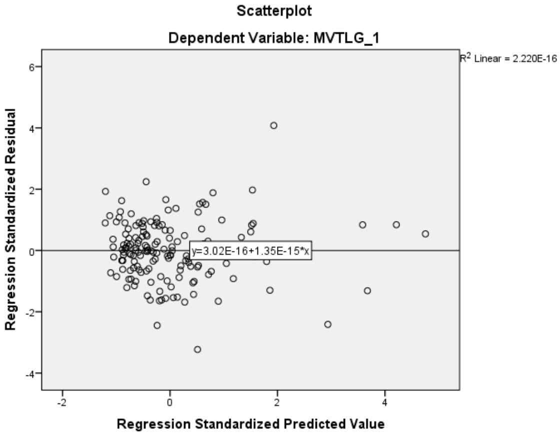


Figure 50. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

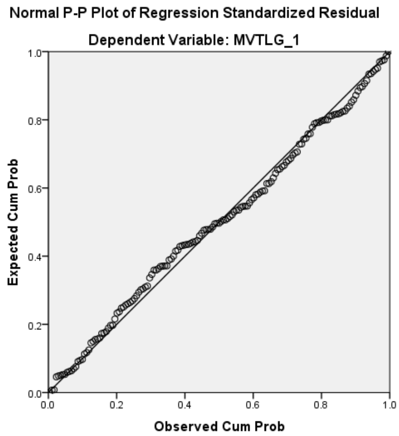


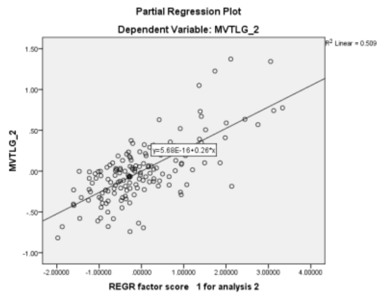
Figure 51. Regression Standardized Residual for dependent variable

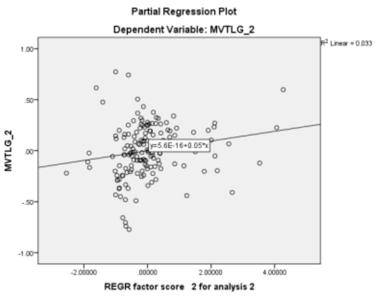
A.3.2 MVT rates during Period Two

Table 18. Estimated coefficients for PC scores for integrated theories in OLS regression models during Period Two

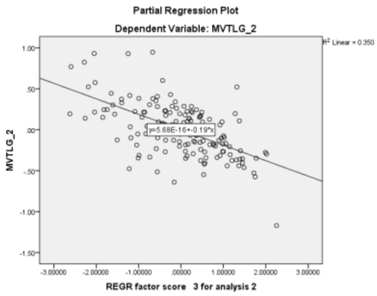
Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.593	0.000	0.021	1.00	1.00
PC2	0.108	0.025	0.021	1.00	1.00
PC3	-0.427	0.000	0.021	1.00	1.00
PC4	0.255	0.000	0.021	1.00	1.00
PC5	0.111	0.021	0.021	1.00	1.00
PC8	-0.194	0.000	0.021	1.00	1.00
Adjusted R^2	0.64				
Durbin-Watson statistic	1.70				
Std. Error of the Estimate	0.26273				

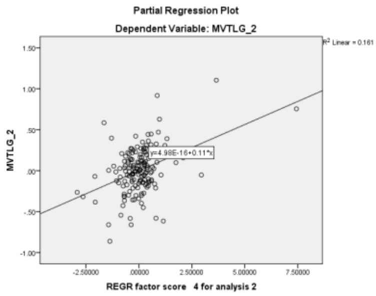
Assumption of the linearity



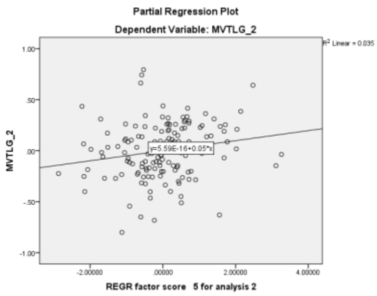


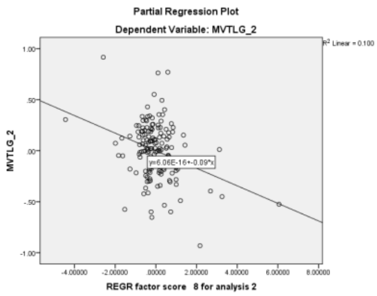
A. PC1 B. PC2





C. PC3 D. PC4





E. PC5 F. PC8

Figure 52. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

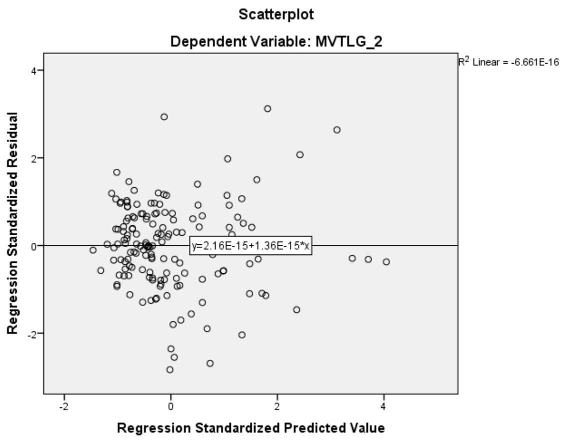


Figure 53. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

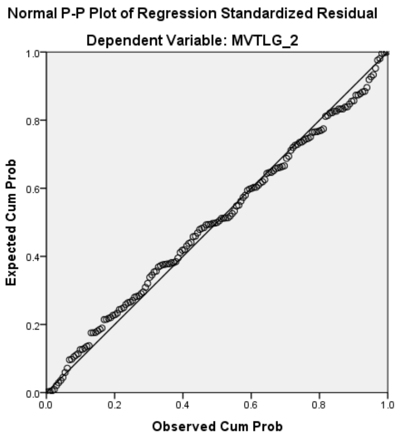


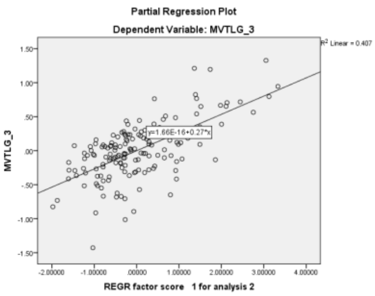
Figure 54. Regression Standardized Residual for dependent variable

A.3.3 MVT rates during Period Three

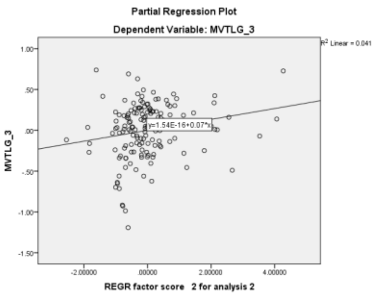
Table 19. Estimated coefficients for PC scores for integrated theories in OLS regression models during Period Three

Variables	Beta	Sig	Std. Error	Collinearity Statistics	
				Tolerance	VIF
PC1	0.552	0.000	0.026	1.00	1.00
PC2	0.137	0.012	0.026	1.00	1.00
PC3	-0.369	0.000	0.026	1.00	1.00
PC4	0.258	0.000	0.026	1.00	1.00
PC8	-0.176	0.001	0.026	1.00	1.00
Adjusted R^2	0.54				
Durbin-Watson statistic	1.56				
Std. Error of the Estimate	0.3207				

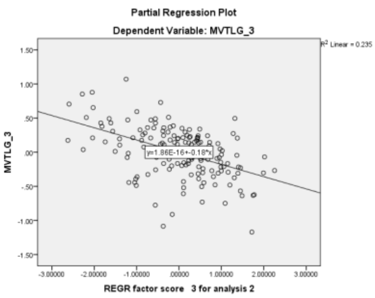
Assumption of the linearity:



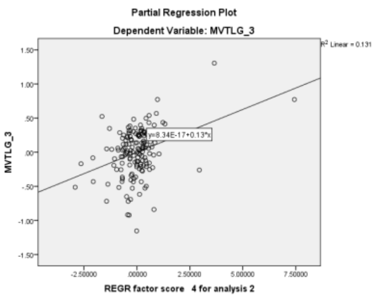
A. PC1



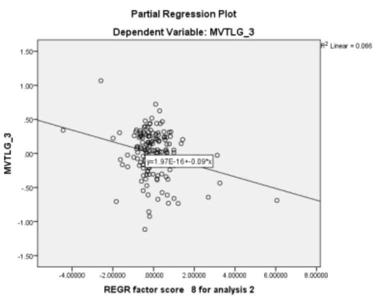
B. PC2



C. PC3



D. PC4



E. PC8

Figure 55. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

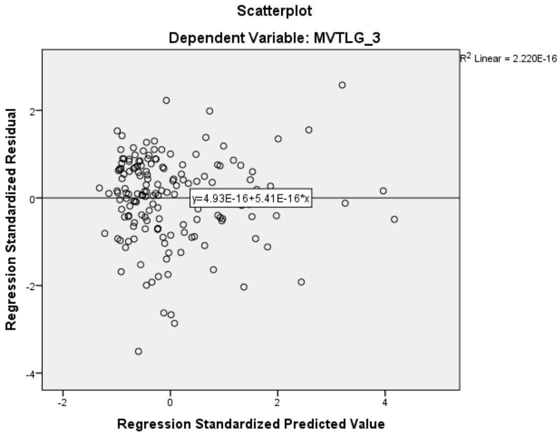


Figure 56. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed

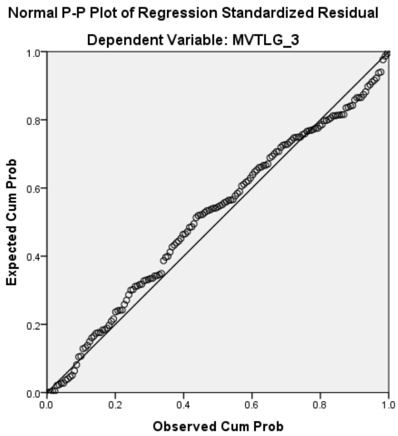


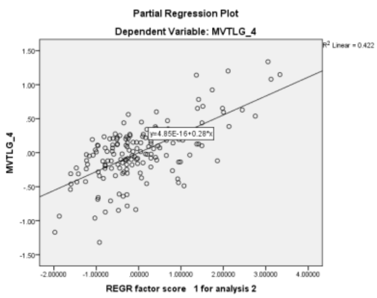
Figure 57. Regression Standardized Residual for dependent variable

A.3.4 MVT rates during Period Four

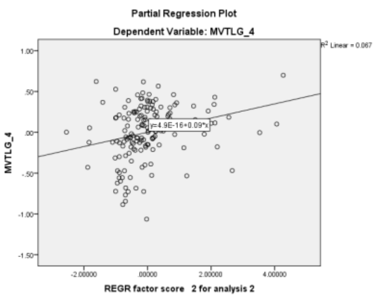
Table 20. Estimated coefficients for PC scores for integrated theories in OLS regression models during Period Four

Variables	**Beta**	**Sig**	**Std. Error**	**Collinearity Statistics**	
				Tolerance	**VIF**
PC1	0.569	0.000	0.026	1.00	1.00
PC2	0.178	0.001	0.026	1.00	1.00
PC3	-0.35	0.000	0.026	1.00	1.00
PC4	0.252	0.000	0.026	1.00	1.00
PC7	0.111	0.042	0.026	1.00	1.00
Adjusted R^2	0.54				
Durbin-Watson statistic	1.41				
Std. Error of the Estimate	0.3307				

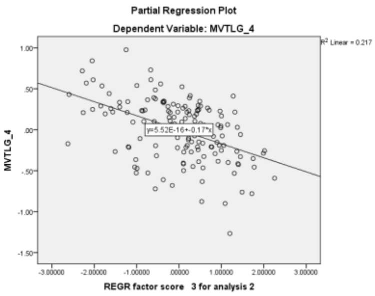
Assumption of the linearity



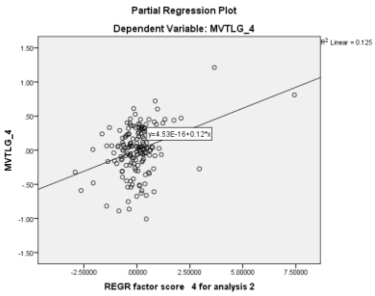
A. PC1



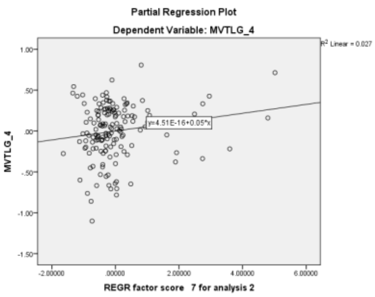
B. PC2



C. PC3



D. PC4



E. PC7

Figure 58. Partial correlation plots between the independent variables and MVT rates

Assumption of homoscedasticity of the model:

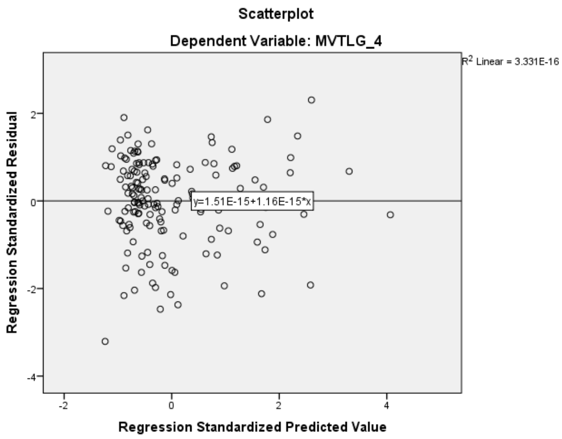


Figure 59. Scatter plot showing the variance of the residuals

Assumption that the residuals are normally distributed:

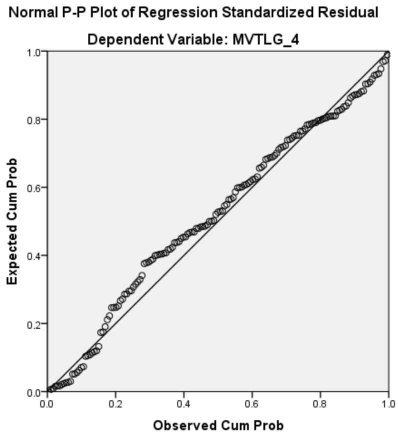


Figure 60. Regression Standardized Residual for dependent variable