THE IMPACT OF OPERATIONAL PERFORMANCE REVIEWS (OPRs) ON REPORTED CRIME IN QUEENSLAND

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EXECUTIVE SUMMARY

- In 1994 the New York City Police Commissioner, William Bratton, implemented a new, strategic approach to crime control and order maintenance that he coined “COMPSTAT.” COMPSTAT is a management strategy that is designed to reduce, prevent and control crime.
- Many proponents have claimed that COMPSTAT made an important contribution to the significant crime drop in New York City during the 1990s.
- Since the first appearance of COMPSTAT in the United States during the mid 1990s, Australian Police Department executives, police ministers and police agency representatives have travelled to New York City to review the COMPSTAT approach, brought the idea back to Australia, and made some changes to suit our local conditions.
- The claim that COMPSTAT and Australian versions of COMPSTAT can reduce crime remains conjecture.
- Our project evaluates the impact of Queensland Police Service’s version of COMPSTAT known as “Operational Performance Reviews” (OPRs). Our study examines the impact of OPRs on reported crime in Queensland and assesses whether or not the OPRs have led to any crime reductions across the 29 police districts in Queensland.
- Our research uses monthly reported crime offence data for the State of Queensland in Australia. We use the State of Queensland as our unit of inquiry in our Stage One analysis and we use the Police Districts as our unit of inquiry in our Stage Two analysis.
- Our statewide impact evaluation of OPRs used a quasi-experimental design to assess the magnitude and direction of the intervention on reported crime incidents.
- The introduction of OPRs was found to be associated with a significant decrease in the total number of reported offences in Queensland. Our time series results show that when reported crime data (1995 to 2004) for the entire State of Queensland are examined and all seasonal, trend, random “noise” (i.e., ad hoc changes in police practice, application of laws, in and out-migration patterns, statewide, ad-hoc crisis etc.) are factored into the model, then the OPRs introduced by the QPS in early 2001 led to a direct and statistically significant decline in crime.
- Had OPRs not been introduced across the State of Queensland in early 2001, we would have predicted a steady, seasonally-based increase in crime. Indeed, by June 2004, the actual number of reported offences was 8495. Without the introduction of OPRs, we could have expected to see the number of reported offences to be around 11,700, ceteris paribus. This is a saving of about 3200 crimes that can be directly attributable to the introduction of OPRs in Queensland.
- OPRs were associated with a significant reduction in unlawful entry offences (unlawful entries into dwellings and other properties). Serious assaults, common assaults, sexual offences, armed robberies, unarmed robberies, and unlawful use of motor vehicle offences all exhibited a non-significant decreases associated with the implementation of OPRs.

- The overall cost-effectiveness of OPRs was evaluated by deriving the ratio of the cost of OPRs to the costs of various crimes. When we weighed these operational costs of OPRs against the savings of reduced crime ($2,773,675), the introduction of OPRs appears to have been cost-effective, resulting in an overall saving of $1,162,175.
- The introduction of OPRs was associated with a statistically significant decrease in unlawful entries into dwellings. This finding is consistent with Chilvers and Weatherburn's (2004) evaluation of the New South Wales equivalent of OPRs in Queensland. Without the introduction of OPRs, we could have expected to see the number of unlawful entries to be almost double the actual figure, ceteris paribus.
- We find that the introduction of OPRs resulted in a "savings" of about $870,000 in the state crime cost of residential burglaries. If the OPRs had NOT been introduced, then the cost of crime to Queensland would have been $1.2 million more in crimes of unlawful entry to commercial/business premises.
- This finding suggests that the problem oriented policing efforts of police in the area of dealing with unlawful entries is likely to be using tactics that are particularly important.
- We note that there was a decline in unlawful entries throughout most of the states in Australia, starting at about the same time that the OPRs were introduced into Queensland. This is a major confounding factor that we cannot directly answer in the present analysis. We suggest that more research needs to be undertaken to understand the drop in crime in Australia, within the context of Australian states introducing COMPSTAT-like initiatives.
- A comprehensive state-by-state analysis of COMPSTAT-like programs in Australia will help to understand the context of the crime drop in Australia and the extent that COMPSTAT-like programs have contributed to this decline.
- The second stage of our analysis involved the application of mixed model statistical techniques to analyse the district-by-district variations in the longitudinal time series data while controlling for socio-structural variables.
- Our results show that some of the Districts with major urbanisation and in-migration experiences over the last ten years confounded the state-wide declines in crime, by consistently posting increases in crime.
- Overall, our mixed model analysis of the impact of OPRs on total reported crime suggests that there a major differences between the districts, that some of the districts are driving the overall state-wide crime reductions, whilst others are confounding the positive effects of implementation of OPRs in Queensland.
- The issue of social disadvantage certainly plays a part in understanding district variations in crime, but not as an overall superior predictor to the OPRs.
- Our total crime model also shows marginal influences of effective leadership, albeit the leadership issue is not a significant predictor.
- The mixed model analysis provides strong evidence for our hypothesis that OPRs can more than compensate for problems of social disadvantage.
- Three major findings emerging from our research: first, the impact of OPRs is different for different categories of crime. Second, the impact of OPRs varies considerably by district. Third, we suspect that there is further variation in the impact of OPRs at the smaller units of analysis (i.e., police divisions) that are potentially influencing statewide trends in data.

INTRODUCTION

In 1994 the New York City Police Commissioner, William Bratton, implemented a new, strategic approach to crime control and order maintenance that he coined "COMPSTAT."[1] COMPSTAT is a management strategy that is designed to reduce, prevent and control crime. It involves executive police officers (Commissioners, Chiefs, Deputy Commissioners) meeting with precinct or district commanders in a high-pressure forum on a regular basis (see Henry, 2002; McDonald, 2002, Silverman, 1999). Overall, COMPSTAT may be viewed as a four-step process including accurate and timely intelligence, rapid deployment, effective tactics, and follow-up and assessment (Walsh & Vito, 2004). During COMPSTAT meetings the participants review district crime statistics, discuss emerging crime problems, identify strategic approaches for controlling crime problems, and discuss progress made during the previous period. Police Executives then set, in consultation with the District Commanders, a series of goals and objectives that must be achieved prior to the next COMPSTAT meeting. In 1996 COMPSTAT won a Harvard University "Innovations in Government Award".

Many proponents have claimed that COMPSTAT made an important contribution to the significant crime drop in New York City during the 1990s (see Bratton, 1997; 1998; Dodenhoff, 1996; Safir, 1998). Popular literature and common opinion among many in the police community is that COMPSTAT can be credited with impressive reductions in crime and improvements in neighbourhood quality of life (Bouza, 1997; Gurwitt, 1998; Kelling & Sousa, 2001; Maple, 1999; Remnick, 1997; Witkin, 1998). Indeed, Silverman and O'Connell (1997) consider COMPSTAT as the "linchpin strategy" that binds together other policing tactics such as zero

[1] The term "COMPSTAT" is shorthand for "computer driven crime statistics." COMPSTAT is, however, much more than police examining crime statistics. For an excellent review of the COMPSTAT model see Bratton, 1998; Vincent, 2002.

tolerance, problem-oriented policing, order maintenance policing and police efforts that seek to reduce crime and improve quality of life.

Since the first appearance of COMPSTAT in the United States during the mid 1990s, Australian Police Department executives, police ministers and police agency representatives have travelled to New York City to review the COMPSTAT approach, brought the idea back to Australia, and made some changes to suit our local conditions (see ABC Lateline, 4 June 1998; Brereton, 1999). The Australian COMPSTAT versions are variously referred to as Operational Performance Reviews (Queensland), Operations Crime Reviews (New South Wales), Corporate Management Group Performance Reviews (Tasmania), Organisational Performance Reviews (Western Australia), COMPSTAT (Victoria) and Performance Outcome Reviews (South Australia). Maas (1998) suggests that this wide diffusion of COMPSTAT across democratic countries in recent years is testament to the faith that police put in the COMPSTAT process for reducing crime problems (see also Weisburd, Mastrofski, McNally, Greenspan & Willis, 2003).

The claim, however, that COMPSTAT and Australian versions of COMPSTAT can reduce crime remains conjecture. Some critics of COMPSTAT doubt the likelihood that COMPSTAT was in fact the “New York Miracle” that many have claimed (see Brereton, 1999; Dixon, 1998; Grabosky, 1999). Magers (2004) argues that police organisations need to foster an atmosphere of ongoing assessment and evaluation of strategies and tactics. It is clear that there is a lack of empirical research that examines the contribution (if any) of COMPSTAT to crime reduction (see Eck & Maguire, 2000, but see Chilvers and Weatherburn, 2004). Thus, one important, yet unanswered, question is how much credit (if any) COMPSTAT (and

Australian versions of COMPSTAT) can be given for declines in crime in cities where it has been implemented.

Our project evaluates the impact of Queensland Police Service's version of COMPSTAT known as "Operational Performance Reviews" (OPRs). Our study examines the impact of OPRs on reported crime in Queensland and assesses whether or not the OPRs have led to any crime reductions across the 29 police districts in Queensland. We begin this report with a synopsis of the background literature that informs our research. In the second part of our report, we describe our data and data extraction and aggregation methods. The third section examines the statewide impact of introducing OPRs in Queensland in 2001. We use interrupted time series analysis to assess and isolate the direct impact OPRs had on different categories of crime across the state. In the fourth part of our report we examine the district-by-district impact of OPRs on different categories of crime. We use a random-effects, mixed model to understand the district variations in crime as a result of introducing the OPRs. We conclude with a discussion of our findings.

BACKGROUND LITERATURE

In the late 1960s and 1970s many police departments in democratic societies were heavily committed to the professional or "reform model" of policing (see Kelling & Moore, 1988). The police drew their legitimacy and authority through the law. By "professionalising" their management practices, they emphasised crime control as the central function of police, they centralised their organisational structures and emphasised crime investigative, rapid response and preventive patrolling activities.

By the mid 1980s, however, every major police strategy to prevent or control crime had been "unmasked" by scientific research (see Bayley, 1994; Weisburd & Eck, 2004) and scholars began to challenge the fundamental premise of whether the police could have a significant impact on crime (see Gottfredson & Hirschi, 1990; Greenwood, Chaiken & Petersilia, 1978; Levine, 1975). In short, while the police had long considered their core role as effective "crime fighters," the scientific evidence seemed to suggest otherwise.

Despite the reluctance of the police to admit that they were largely ineffective during the 1970s and 1980s in reducing crime, it is clear that policing has undergone significant change during the 1990s and now into the 21st century. External factors such as the global threat of terrorism (Australian Government, 2004), global trends in governance (see Ayres & Braithwaite, 1992), pressure from the growing private security sector (Prenzler & King, 2002; Shearing & Stenning, 1987), pressure from a demanding public, and dramatic innovations in technology have created enormous pressure on the police to "do more with less" and be more effective in their core business of crime control and crime prevention.

Police departments around the world have now changed their emphasis from an almost exclusive focus on reacting to crimes after they have been committed to being more effective in controlling crime and embracing crime prevention and problem-oriented policing as central to their mission. In this transformation, the police have become more consultative with community members and stakeholders, they have re-engineered their police organisations to become more operationally accountable (see McDonald 2002) and they have adopted a variety of new approaches to policing (Bayley, 1994; Eck & Spelman, 1987; Goldstein, 1990; Kelling & Moore, 1988; Mazerolle & Ransley, 2006; Skogan & Hartnett, 1997).

There is now a growing body of scientific evidence to suggest that the police can indeed be effective at reducing crime problems (see Bayley, 1998, Eck & Maguire, 2000; Mazerolle, Soole & Rombouts, 2005; Sherman, Gottfredson, MacKenzie, Eck, Reuter, & Bushway, 1997; Weisburd & Eck, 2004) and there seems to be no shortage of diffusion of knowledge about trends in operational police practice (see for example Weisburd et al., 2003).

One of the major trends in police management that has swept across democratic societies since the mid-1990s has been the adoption of COMPSTAT and COMPSTAT-like programs. COMPSTAT originated in New York City in 1994 under then Police Commissioner William Bratton. At the core of the approach are four crime reduction principles: (1) accurate and timely intelligence about crime made available at all levels in the organization, (2) selection of the most effective tactics for specific problems, (3) rapid deployment of people and resources to implement those tactics, and (4) "relentless" follow-up and assessment to learn what happened and make subsequent tactical adjustments as necessary (Bratton, 1998; Maple, 1999; McDonald, 2002; Silverman, 1999).

The widespread popularity and appeal of COMPSTAT is perhaps unprecedented in recent police history. Mark Moore states that "…Commissioner Bratton's bold statement – reacceptance of responsibility for controlling crime – was a very important moment in leadership of the criminal justice system" (1997, p.67). Journalists such as Dodenhoff (1996), Witkin (1998) and Remnick (1997) seem convinced that COMPSTAT led to reductions in crime in New York City; police leaders such as Bill Bratton as the "author" of COMPSTAT (1997, 1998), Howard Safir (1998), and Tony Bouza (1997) hail COMPSTAT as the answer to all contemporary crime problems; Bratton's right-hand man and arguably the person who drove most of COMPSTAT in NYC in the early days, Jack Maple (1999) was certain COMPSTAT was the answer to rising crime problems in NYC; and other New York City based authors such as Vince Henry (2002), Phyllis McDonald (2002), Eli Silverman (1999) as well as Bratton's long term confidant George Kelling (see Kelling & Sousa, 2001) argue strongly that COMPSTAT will lead to reductions in crime not just in New York City but also in other cities around the world.

Others are not so convinced. John Eck and Ed Maguire (2000) carefully examined New York City's homicide data and concluded that

> "…the implementation of COMPSTAT in New York in 1994 cannot be credited independently with the decline in homicides in that city…[and] that other changes in New York City's policing practices implemented around the same time as Compstat (e.g zero tolerance policing) cannot [also] not be given credit for the decline. [Moreover] the diffusion of the Compstat process to other cities throughout the United States came too late to have produced the national decline in homicides" (pp. 234-235).

Similarly, Rosenfeld, Fornango, and Baumer (2005) recently concluded that no evidence could be found to support an impact of COMPSTAT on homicide trends. In Australia, David Dixon (1998) and David Brereton (1999) are equally sceptical of the ability of COMPSTAT to reduce crime. Dixon (1998) points to the relationship between the decline in the crack cocaine epidemic and the falling murder rate. Brereton (1999) examines both violent crime and burglaries across five major cities in the US and similarly concludes that there is "little evidence to support claims for New York exceptionalism" (page 8). In contrast, recently Australian researchers, Chilvers and Weatherburn (2004), evaluated the impact of "Operation and Crime Review (OCR) Panels:" New South Wales' version of COMPSTAT. Employing time series analysis, they found a significant reduction in robberies, break-and-enters and motor vehicle thefts attributable to the introduction of OCR panels. The OCRs had the strongest effect on break-and-enter offences (Chilvers & Weatherburn, 2004).

Despite the debate surrounding the effectiveness of COMPSTAT to reduce crime, many police agencies in the US, UK and Australia have adopted, adapted and implemented COMPSTAT-like programs. To explore this diffusion of the COMPSTAT approach, David Weisburd and his colleagues from the Police Foundation (2001) conducted a survey in 1999 across a stratified sample of American police agencies with municipal policing responsibilities (Weisburd, Mastrofski, McNally, & Greenspan, 2001). A mail survey was sent to all randomly selected police agencies with over 100 sworn police officers and to a sample of 100 agencies with 50-99 sworn officers. From the survey conducted by Weisburd and his colleagues six key elements emerged as central features of COMPSTAT programs across the United States: mission clarification; internal accountability; geographic organization of command; organizational flexibility; data driven problem identification and assessment; and innovative problem solving.

Queensland's version of COMPSTAT, known as Operational Performance Reviews (or OPRs for short), encapsulate many of these key elements of COMPSTAT. Commissioner Atkinson initiated the Operational Performance Review (OPR) process in early 2001 and sought to closely integrate the QPS version of problem-oriented policing that they call Problem-Oriented and Partnership Policing (POPP) within the OPR process. The Commissioner articulated that the OPRs should focus (at least in the initial implementation period[2]) on five priorities. These included: public safety (reducing offences against the person, domestic violence and traffic

[2] The OPRs were initially implemented in August, 2001. Hum,an Resource Management, Financial Management and Professional Standards and Ethical Practice were included in the reviews from February/March, 2002. Corporate level commands, including State Crime Operations Command and Operations Support Command were introduced in 2003 and in 2004 the Administration Division and Information Management Division were included.

safety offences), reducing property crime (including unlawful entry offences and unlawful use of motor vehicles), reducing and better handling calls for service; better handling of major planned and unplanned events; and getting a better handle on unique District issues. These unique district issues could range from drug problems, to drinking in public issues to whatever crime and quality of life problems that seemed to plague each individual district.

OPR meetings in Queensland are chaired by Commissioner Atkinson and assisted by both Deputy Chief Executives (Operations and Resource Management). Assistant Commissioners from the Operations Support Command and State Operations Support Command also attend the OPR forums. District Officers attend the OPR meetings accompanied by their respective regional Assistant Commissioner, the Chief Superintendent from the region, as well as expert support personnel (such as regional intelligence coordinators, regional crime coordinators and traffic coordinators). The meetings run for about 2 hours and all presentations of data are made in powerpoint format.

In our evaluation of OPRs in Queensland, we focus on the impact of OPRs on reported crime both across the state of Queensland as well as between and within the 29 police districts[3]. We specifically examine the impact of OPRs on the five priority areas identified by Commissioner Atkinson. Our central research question is: What impact did the introduction of OPRs in Queensland have on reported crime? What impact did the introduction of OPRs have on specific categories of crime, particularly those categories of crime identified as priority issues from the outset (i.e., public

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[3] We note that the Crime and Misconduct Commission is currently completing a parallel, process evaluation of OPRs in Queensland using case studies of three police districts to consider what extent, and how, has the introduction of the OPRs promoted intelligence-led, and problem-oriented policing in the Queensland Police Service? to what extent, and how, has the introduction of the OPRs influenced both strategic and day-to-day management within the Queensland Police Service? and how the OPRs can enhance complaints management and risk management in respect of professional standards and ethical practice in the Queensland Police Service?

safety including reducing offences against the person, domestic violence and traffic safety offences, reducing property crime including unlawful entry offences and unlawful use of motor vehicles)? Are there differences in the effectiveness of OPRs in reducing crime problems across the 29 police districts in Queensland?

STAGE ONE ANALYSIS: STATEWIDE IMPACT OF OPRs

Data

Our research uses monthly reported crime offence data for the State of Queensland in Australia.[4] The data provided by the Queensland Police Service (QPS) were gathered in the form of monthly counts of offences (by "Crisp Codes") for each Police Division (N = 295) in Queensland from July 1995 to June 2004. In total, there were 108 observation points: 73 pre-OPR monthly counts and 35 post-OPR monthly counts. The data for each of the 295 police divisions were assigned to the appropriate Police District (N = 29). We use the State of Queensland as our unit of inquiry in our Stage One analysis and we use the Police Districts as our unit of inquiry in our Stage Two analysis. It is at the District level of aggregation that the OPR fora are conducted. Appendix A contains a map of all police districts as well as district characteristics such as geographic size and number of police personnel.

While OPRs were introduced to different police regions at different points in time, the date chosen for the statewide analysis (August, 2001) was the earliest date of implementation. We use the earliest date as our point of "interruption" because all District Commanders were informed of the innovation at this time. We expect that the

[4] We note the limitations of using reported crime offence data in criminological research. Low reporting rates for some categories of crime, inaccuracies in the data records (e.g. incorrect crime offence dates, non-existent locations, incorrect crime category codes, changes over time in reporting and coding practices etc) as well as administrative errors all comprise potential limitations with the QPS crime offence data. Nonetheless, the crime offence data used in our research comprise the most scrutinised data used by the police in Queensland and are considered, at least in the State of Queensland, as being the "best" indicator of crime available.

communication and extensive consultation about the introduction of the OPRs would have created what is known as an “announcement effect” (Smith, Clarke, & Pease, 2002) such that District Commanders would have altered their management and operational strategies at this time.

Once the data were obtained from the QPS the 60 crisp codes for different offences were collapsed to create 13 different crime types (see Appendix B[5]). These offence categories were checked with QPS researchers to ensure their conceptual validity. A subset of the data for different offence types and time periods was independently checked to assess the accuracy of the police department data extraction and their aggregation processes.

Our Analytic Approach

Our statewide impact evaluation of OPRs used a quasi-experimental design to assess the magnitude and direction of the intervention on reported crime incidents. Time series analysis is considered to be a strong quasi-experimental design (Cook & Campbell, 1979) and is a popular method used to examine the impact of legal interventions (see for example, White, Fyfe, Campbell, & Goldkamp, 2003). There are several reasons why interrupted time series is a useful and appropriate technique to assess the impact of an intervention. First, oftentimes it is difficult to identify adequate matched control groups when an innovation is introduced. In time series analysis, serial data (number of crimes) collected at consistent intervals (e.g. month) act as their own control. Second, Glass (1997) notes that time series analysis is particularly suitable when an intervention has been introduced by someone other than

[5] Our results present the findings from our analysis of both serious and less serious crime in Queensland. From the outset, however, we did not expect the time series observations for homicide-related offences to be appropriate for ARIMA intervention analysis. On examination of the data, we understood that the homicide-related offense data already approximated ‘white noise’. In essence, a (0,0,0) model was the most appropriate model for these data. The introduction of OPRs resulted in a non-significant decrease in homicide-related offences (-0.286, p = 0.787).

the researcher (in this case, the police), the intervention was not introduced for the purposes of research (OPRs were primarily introduced to improve police efficiency), and the data used for evaluation comes from archives gathered routinely for administrative purposes (i.e., reported crimes). Finally, another advantage of time series analysis over traditional regression techniques is its ability to account for the serial dependence that often occurs in time series data (McDowall, McCleary, Meidinger, & Hay, 1980). Traditional linear techniques fail to take these processes into account and therefore often over-estimate the impact of an intervention. The time series approach allows the researcher to model, and therefore removes the effects of, the particular patterns or "noise" that may be present in time series observations. This allows for a clearer picture of the independent effects of the intervention.

The primary assumption of time series analysis is that the series of observations is stationary. As with other statistical procedures the series need to have a constant mean and variance. The possible sources of "noise" that exist in time series observations all serve to make the observations dependent on each other and cause the series to become non-stationary. An integrated process (known as a random walk; the "d" component) involves random shocks that enter the series and accumulate or integrate over time. This process can be modelled by "differencing" the series (subtracting the first observation from the second etc.). For example, an increasing linear trend in the data (e.g., increasing crime rates) is illustrative of a time series that requires differencing. An autoregressive process (the "p" component) involves random shocks entering the time series model and leaking out exponentially. For example, the number of offences in July of any year could be influenced by the number of offences in the preceding months. A moving average process (the "q" component) occurs when random shocks enter the system and persist for q observations before leaking out. For example, the homicide totals from previous months help determine each month's homicide total. Seasonal patterns may also exist, corresponding to seasonal integrated (D), autoregressive (P), and moving average (Q) processes. Essentially, ARIMA (Auto Regressive Integrated Moving Average) time series modelling involves estimating the particular (p,d,q)(P,D,Q) processes for a given set of observations.

The aim of the time series approach was to isolate and evaluate the direct impact of the implementation of OPRs on reported offences in Queensland. To accomplish this task, SPSS ARIMA interrupted time series analysis was used to analyse the effect of OPRs on reported offences over time. This consisted of two main stages: (1) model-building to identify the patterns occurring in the frequency of offences and (2) impact assessment to determine whether changes in reported offences were associated with the implementation of OPRs.

The model-building component of time series analysis essentially involved three steps. The first step was the identification of the particular processes that may exist in the data. This was done by comparing patterns of autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) to patterns known to correspond to integrated, autoregressive, and moving average processes. Once the model was identified, the parameters of each process were estimated. In this stage the parameters must be statistically significant and not violate assumptions[6]. The diagnosis phase involved an examination of the residuals of the model to ensure that they were normally distributed and within their standard error limits (thereby approximating "white noise"). An ACF/PACF pattern for the residuals is obtained to ensure that the residuals are not significantly different from zero and the residuals are

[6] Moving average processes must be within the 'bounds of invertibility' while autoregressive processes must be within the 'bounds of stationarity'. Both assumptions refer to the coefficients being constrained to the interval of -1 to +1.

plotted against time to assess variance stationarity. Non-stationarity of variance occurs when the residuals of a given model do not appear to have a constant variance. In this situation, a transformation is normally required. The presence of outliers may have a substantial impact on time series analysis and can be identified through inspection of the raw time series plots and model residuals (Tabachnick & Fidell, 2001). When outliers were identified, the value was replaced with the mean of the preceding and following month. For example, if an outlier was identified in September 1996, it was replaced with the mean of August and October 1996.

In order to conduct the impact assessment an initial model was developed based upon the pre-intervention time series observations. Once an adequate model of the "noise" had been constructed the post-intervention observations were included in order to more accurately assess the impact of OPRs. Time series forecasting was used to provide a graphical display of the effectiveness of OPRs. Once a model for a particular crime type had been developed based on the pre-OPR time series, this pre-OPR model was used to obtain predicted values corresponding to the post-OPR time period. When plotted against the actual reported offences in the post-intervention period it enabled a visual comparison of "what would have likely happened" versus "what actually happened" in terms of reported offences[7].

As a scoping exercise, the monetary "savings" of reduced crime due to OPRs were calculated to contextualise the results in terms of their practical significance. Mayhew (2003) provides estimates of the average cost of an individual type of offence taking into account both tangible and intangible costs. These figures were adapted for the current study to derive an estimate of the total cost savings in crime occurring the post-OPR period. In order to calculate the "savings" attributable to

[7] It should be noted that forecasting is not possible if the time series has been differenced. In this situation, the forecasting process simply plots a constant mean for the pre-OPR time series.

OPRs the costs for an average crime incident were multiplied by the OPR coefficient produced in the time-series analysis. “Savings” were produced for eight individual crime types for which costs were available. Overall cost-effectiveness of OPRs was evaluated by deriving the ratio of the cost of OPRs to the costs of various crimes.

Results

Total Reported Offences

Arguably our most important analysis focused on the impact of OPRs on the total amount of reported offences across the State of Queensland. Inspection of the pre-OPR time series observations revealed an increasing linear trend as well as a seasonal component with peaks at around January to April (Summer) of each year. This suggested that the pre-OPR time series observations required both regular and seasonal differencing. Examination of the ACF/PACF pattern after regular and seasonal differencing revealed negative ACF spikes at lag (1) and lag (12) indicating both regular and seasonal moving average components. There was also a large positive ACF spike at lag (11). The PACF plot revealed a higher-order moving average component (q = 2) due to the largest spike occurring at lag (2). An ARIMA (0, 1, 2) $(0, 1, 1)_{12}$ model for pre-OPR time series observations was specified and all components of this model were significant. The ACF/PACF plot of the residuals of this model revealed that the residuals appeared to approximate “white noise”. None of the residuals were significant nor exceeded the standard error limits. The residuals were plotted against time and revealed a possible outlier (July 1997). This raw time series observation corresponding to July 1997 was replaced and the analysis was performed with the replaced value. However, this made little difference to the results and therefore the original July 1997 value was retained for impact assessment.

Once the pre-OPR time series observations had been adequately modelled, the intervention component was then added to the model. All components of this model were significant. Inspection of the residuals for this model revealed that all fell approximately within two standard error limits and were non-significant. The residuals were plotted against time and again revealed the spike at July 1997. Table One presents the parameter estimates for total reported offences.

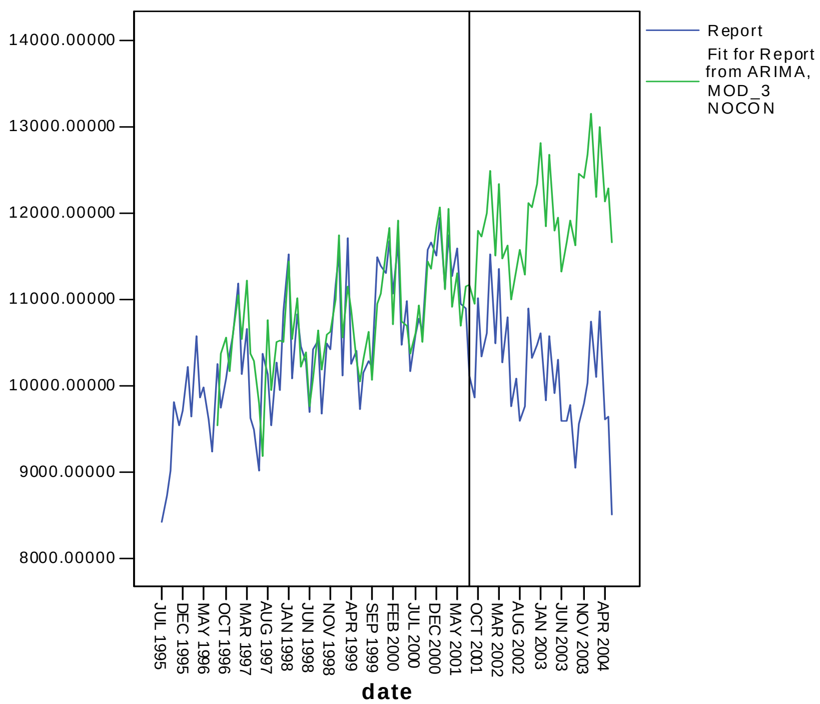
Table 1: Parameter Estimates for Total Reported Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
MA1	.53 (.15)	3.56	.00
MA2	.38 (.14)	2.68	.01
SMA1	.84 (.39)	2.13	.04
Post-intervention			
MA1	.40 (.10)	4.01	.00
MA2	.26 (.10)	2.65	.01
SMA1	.93 (.36)	2.57	.01
OPR	-972.32 (278.86)	-3.49	.00
Model-fitting information			
Akaike's Information Criterion			1397.83
Schwarz's Bayesian Criterion			1408.04
Likelihood ratio test			-694.91
Residual variance			109222.58
Standard error			330.49

As Table One shows, once the series was regularly and seasonally differenced and regular and seasonal moving average components were modelled adequately, the introduction of OPRs was found to be associated with a significant decrease in the total number of reported offences in Queensland. This is an important policy finding. What our time series results show is that when reported crime data (1995 to 2004) for the entire State of Queensland are examined and all seasonal, trend, random "noise" (i.e., ad hoc changes in police practice, application of laws, in and out-migration patterns, statewide, ad-hoc crisis etc.) are factored into the model, then the OPRs introduced by the police department in early 2001 led to a direct and statistically significant decline in crime.

To visualise the amount of crime reduced directly by the OPRs, we used time series forecasting techniques to plot the predicted crime rate assuming OPRs had not been introduced against the actual crime rate post OPR implementation. Our time series forecasting models were used to obtain predicted values for the post-OPR time series observations based upon the pre-OPR ARIMA model. These values were then plotted against the observed reported offences for the post-OPR time series observations (see Figure 1). Note that the green line represents the predicted values of total reported offences estimated from the pre-OPR time series while the blue line represents the actual total reported offences after implementation of OPRs.

Figure 1: Forecasted versus Actual Total Reported Offences in Queensland



As Figure One shows, had OPRs not been introduced across the State of Queensland in early 2001, we would have predicted a steady, seasonally-based increase in crime. Indeed, by June 2004, the actual number of reported offences was 8495. Without the introduction of OPRs, we could have expected to see the number of reported offences to be around 11,700, ceteris paribus. This is a saving of about 3200 crimes that can be directly attributable to the introduction of OPRs in Queensland (see later for our cost effectiveness analysis).

In the sections below, we build a story as to what types of offences have largely contributed to the decline in crime attributable to the introduction of the OPRs in Queensland. We focus on 13 offences that represent the primary offences that the Police Department identified as priority offences. Details of the categories and definitions of these crime types can be found in Appendix B.

Dangerous Driving Offences

The pre-OPR time series observations for dangerous driving offences did not exhibit a linear or seasonal trend while the ACF/PACF pattern revealed negative spikes at ACF lag (1) and lag (13). This was indicative of an autoregressive component. The pre-OPR observations were best described by an AR(2) model as all residuals were non-significant and within standard error limits. Once the OPR was added to the model, a third-order autoregressive component was needed to make the residuals non-significant. Intervention analysis using an ARIMA (3,1,0) model revealed that OPRs did *not* have a significant impact on reported dangerous driving offences. Table 2 below, summarizes the dangerous driving results.

Table 2: Parameter Estimates for Reported Dangerous Driving Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.92 (.11)	-8.44	.00
AR2	-.41 (.11)	-3.77	.00
Post-intervention			
AR1	-.95 (.09)	-10.3	.00
AR2	-.73 (.11)	-6.53	.00
AR3	-.37 (.09)	-4.02	.00
OPR	3.04 (2.24)	1.36	.18
Model-fitting information			
Akaike's Information Criterion			582.40
Schwarz's Bayesian Criterion			593.10
Likelihood ratio test			-287.20
Residual variance			12.89
Standard error			3.60

Unlawful Use of Motor Vehicle Offences

Inspection of the pre-OPR time series observations revealed the presence of a quadratic trend with reported offences initially decreasing and then increasing from 1999 onwards. There was also evidence of seasonality with peaks in January to April of each year. Inspection of the ACF/PACF pattern after regular (d=2) and seasonal differencing displayed both regular and seasonal autoregressive processes. An ARIMA $(2,2,0)(1,1,0)_{12}$ was specified and the residuals of this model were all non-significant and within their standard error limits. The introduction of the post-OPR observations required that the model be changed to a moving average process, resulting in an ARIMA $(0,2,1)(1,1,0)_{12}$ model specification. While the residuals of this model approximated 'white noise', there appeared to be non-stationarity of variance, which no transformation could remedy. Table 3 presents the results of the unlawful use ARIMA findings. Overall, the results suggested that OPRs were associated with a non-significant decrease in unlawful use of motor vehicle offences.

Nonetheless, a reduction of 28.56 motor vehicle offences translates into a "cost saving" of about $186,675.

Table 3: Parameter Estimates for Reported Unlawful Use of Motor Vehicle Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.61 (.12)	-4.98	.00
AR2	-.41 (.12)	-3.42	.00
SAR1	-.46 (.13)	-3.63	.00
Post-intervention			
MA1	.95 (.09)	10.81	.00
SAR1	-.42 (.09)	-4.54	.00
OPR	-28.56 (93.82)	-.30	.76
Model-fitting information			
Akaike's Information Criterion			1170.89
Schwarz's Bayesian Criterion			1178.52
Likelihood ratio test			-582.45
Residual variance			13829.72
Standard error			117.60

Serious Assaults

The pre-OPR time series observations for serious assaults revealed an increasing linear trend and seasonality in the form of peaks in October to January of each year. After regular and seasonal differencing, the ACF/PACF pattern revealed large negative spikes at ACF lag (1) and lag (12), indicating both regular and seasonal moving average components. After model estimation, both components were significant and all but one residual (lag (14) did not exceed standard error limits. Once the OPR was added to the model, the seasonal moving average component was non-significant and close to the bounds of invertibility. A seasonal autoregressive component was instead added to the model. All residuals were non-significant except for lag (24). A higher order seasonal autoregressive component (AR2) was therefore added to the model; however, this produced little change so the most parsimonious model was retained – an ARIMA $(0,1,1)(1,1,0)_{12}$ model. Table 4, below presents the results. The results showed that serious assaults exhibited a non-significant decrease associated with the introduction of OPRs.

Table 4: Parameter Estimates for Reported Serious Assaults

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
MA1	.65 (.09)	6.91	.00
SMA1	.82 (.31)	2.67	.01
Post-intervention			
MA1	.66 (.08)	4.01	.00
SAR1	-.51 (.10)	-5.31	.00
OPR	-34.11 (36.08)	-.94	.35
Model-fitting information			
Akaike's Information Criterion			1050.62
Schwarz's Bayesian Criterion			1058.29
Likelihood ratio test			-522.31
Residual variance			3449.98
Standard error			58.74

Common Assaults

The pre-OPR time series observations for reported common assaults displayed a linear trend as well as seasonal variation (peaks in November to March of each year). There also appeared to be an unusual drop in around May, 1997. After regular and seasonal differencing, the ACF/PACF pattern revealed negative spikes at ACF lag (1) and lag (12) suggesting regular and seasonal moving average components. These components emerged as significant during parameter estimation and all residuals of the model were non-significant and within standard error limits. These components remained significant with the introduction of OPRs into the ARIMA $(0,1,1)(0,1,1)_{12}$ model and all residuals remained non-significant. Table 5 presents the results. The results demonstrated a non-significant decrease of common assaults associated with the implementation of OPRs. While both serious and common assaults did not appear to be significantly affected by OPRs, the “savings” in non-significant decreases of assaults amounted to $120,600.

Table 5: Parameter Estimates for Reported Common Assaults

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
MA1	.54 (.11)	5.03	.00
SMA1	.69 (.22)	3.12	.00
Post-intervention			
MA1	.61 (.08)	7.81	.00
SMA1	.87 (.20)	4.35	.00
OPR	-35.98 (33.33)	-1.08	.28
Model-fitting information			
Akaike’s Information Criterion			999.61
Schwarz’s Bayesian Criterion			1007.27
Likelihood ratio test			-496.81
Residual variance			1750.50
Standard error			41.84

Sexual Offences

Inspection of the raw time series revealed a slightly increasing linear trend and a seasonal pattern with peaks in October of each year. After regular and seasonal differencing, the ACF/PACF pattern revealed a negative spike at lag (1) and the largest PACF negative spike at lag (2), suggesting an autoregressive process. An ARIMA $(2,1,0)(1,1,0)_{12}$ model provided the best fit to the pre-OPR time series data with the residuals being non-significant and within their standard error limits. Table 6 presents the results. The results demonstrate that OPRs were associated with a non-significant decrease in reported sexual offences. From a practical perspective, however, this non-significant reduction resulted in a “saving” of $295,000.

Table 6: Parameter Estimates for Reported Sexual Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.63 (.12)	-5.33	.00
AR2	-.43 (.12)	-3.67	.00
SAR1	-.35 (.14)	-2.55	.01
Post-intervention			
AR1	-.60 (.09)	-6.44	.00
AR2	-.42 (.09)	-4.45	.00
SAR1	-.51 (.11)	-4.63	.00
OPR	-117.84 (88.66)	-1.33	.19
Model-fitting information			
Akaike's Information Criterion			1209.48
Schwarz's Bayesian Criterion			1219.69
Likelihood ratio test			-600.74
Residual variance			18176.37
Standard error			134.82

Armed Robbery

ARIMA intervention analyses were conducted separately on armed and unarmed robbery offences reported in Queensland. The pre-OPR time series displayed a linear trend and a possible lower outlier (December, 1996). After regular differencing, the ACF/PACF pattern revealed a negative spike at ACF lag (1) with the largest PACF spike at lag (2). A second-order autoregressive component was therefore specified. The estimation of the pre-OPR model found both autoregressive components to be significant, however, the residuals of this model revealed a pattern of increasing variance over time (i.e., variance non-stationarity). The outlier was therefore replaced with the mean of the preceding and following month. An ARIMA (2,1,0) model was fit to the pre-OPR time series and the residuals of this model approximated 'white noise'. However, the residuals still appeared to display non-stationarity of variance due primarily to a lower outlier in the post-OPR time series observations (September 2003). The outlier was replaced and the resulting residuals displayed stationarity of variance. When the OPR was added to this model, the AR1 and AR2 components remained significant, however, the OPR coefficient was non-significant. Table 7 describes these results. The residuals of this model approximated white noise while the results demonstrated a non-significant decrease of armed robberies associated with implementation of OPRs.

Table 7: Parameter Estimates for Reported Armed Robberies

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.65 (.10)	-6.31	.00
AR2	-.50 (.10)	-4.88	.00
Post-intervention			
AR1	-.63 (.09)	-7.10	.00
SMA1	-.44 (.09)	-5.02	.00
OPR	-10.97 (10.3)	-1.06	.29
Model-fitting information			
Akaike's Information Criterion			855.84
Schwarz's Bayesian Criterion			863.47
Likelihood ratio test			-424.92
Residual variance			168.47
Standard error			12.98

Unarmed Robbery

The pre-OPR time series observations revealed a slight decreasing linear trend that did not require differencing. The ACF/PACF pattern showed a positive spike at ACF lag(1), suggesting an autoregressive component. An ARIMA (2,0,0) model was the best fit to the pre-OPR data with the residuals being non-significant and within their standard error limits. This model was also found to be an appropriate fit when the OPR was added. Table 8 presents the results. The results demonstrated that the introduction of OPRs were associated with a non-significant decrease in unarmed robberies. Overall, the decreases in both armed and unarmed robberies resulted in a “saving” of $68,400.

Table 8: Parameter Estimates for Reported Unarmed Robberies

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	.56 (.11)	5.26	.00
AR2	.43 (.11)	3.96	.00
Post-intervention			
AR1	.56 (.09)	6.27	.00
AR2	.43 (.09)	4.88	.00
OPR	-8.31 (14.96)	-.56	.58
Model-fitting information			
Akaike's Information Criterion			917.39
Schwarz's Bayesian Criterion			925.43
Likelihood ratio test			-455.69
Residual variance			268.94
Standard error			16.40

Ill Treatment of Children Offences

The pre-OPR time series observations revealed a slight increasing linear trend and a possible outlier (September, 1996). The ACF/PACF pattern revealed negative spikes at ACF lag(1) and lag(13) with the largest PACF spike at lag(2), suggesting a higher-order autoregressive component. An ARIMA (2,1,0) model appeared to be the best fit for the pre-OPR time series observations, with all residuals being non-significant and only one exceeding the standard error limits. However, when the OPR was added to this model, the residuals appeared non-stationary in their variance. This was primarily due to the higher number of offences from October, 2003, onwards compared to the rest of the series. Transformation of the data improved the residuals somewhat; therefore the results from the transformed data are presented.

We note that in 2004 there were major changes throughout the State of Queensland in handling child safety issues. This was primarily due to the Crime and Misconduct Commission's Protecting Children report (CMC, 2004) that resulted in a number of recommendations for reform of the child safety system. In 2004/2005,

$91,312,107 was provided by the State Government to implement the entirety of this report's recommendations. Since our impact evaluation of the OPRs did not include the period of time when these major policy and organisational changes were taking place, we feel confident to assume that our assessment of the impact of the OPRs was not confounded by these child safety changes in Queensland.

Table 9: Parameter Estimates for Reported Ill Treatment of Children Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.46 (.11)	-4.05	.00
AR2	-.34 (.11)	-3.01	.00
Post-intervention			
AR1	-.46 (.09)	-4.90	.00
AR2	-.29 (.09)	-3.12	.00
OPR	.25 (.35)	.72	.47
Model-fitting information			
Akaike's Information Criterion			110.70
Schwarz's Bayesian Criterion			118.72
Likelihood ratio test			-52.35
Residual variance			.16
Standard error			.40

Menacing Person Offences

Our category of "menacing persons" included being armed so as to cause fear, stalking, and other offences against the person apart from physical and sexual assaults. Inspection of the pre-OPR time series observations revealed an increasing linear trend. Additionally, there appeared to be a seasonal trend in the form of peaks occurring in November to March of each year. After regular and seasonal differencing, the ACF/PACF pattern displayed negative spikes at ACF lag (1), (7), (12), (15), and (20) while large PACF spikes were present at lag (2) and lag (12). This pattern was suggestive of both regular and seasonal autoregression. An ARIMA (3,1,0)(1,1,0)$_{12}$ was the best fit for the pre-OPR time series observations. All residuals with the exception of lag (15) were non-significant and within their standard error limits. Table 10 describes the results. The results showed that the introduction of OPRs was associated with a non-significant increase in menacing person offences.

Table 10: Parameter Estimates for Reported Menacing Person Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.51 (.12)	-4.11	.00
AR2	-.53 (.13)	-4.11	.00
AR3	-.28 (.13)	-2.21	.03
SAR1	-.54 (.12)	-4.43	.00
Post-intervention			
AR1	-.54 (.10)	-5.19	.00
AR2	-.46 (.11)	-4.30	.00
AR3	-.28 (.11)	-2.63	.01
SAR1	-.55 (.09)	-5.80	.00
OPR	32.04 (21.03)	1.52	.13
Model-fitting information			
Akaike's Information Criterion			940.52
Schwarz's Bayesian Criterion			953.29
Likelihood ratio test			-465.26
Residual variance			1053.40
Standard error			32.46

Unlawful Entry - Dwelling

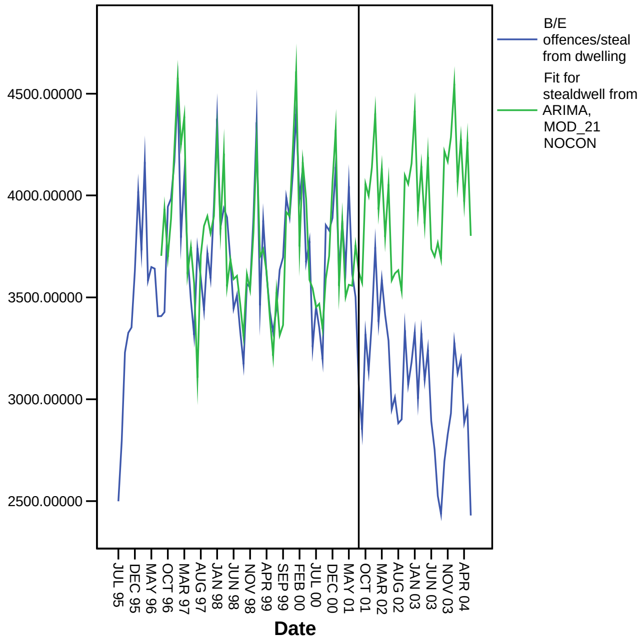
The pre-OPR time series observations did not display a linear trend but did display seasonality in the form of peaks in January to April of each year. After seasonal differencing, the ACF/PACF pattern revealed a negative spike at ACF lag(1) and positive spikes at lags (11) and (12). This pattern was indicative of a regular moving average component and seasonal autoregression. An ARIMA $(0,1,1)(1,1,0)_{12}$ was specified and its coefficients were significant. The residuals of this model were all non-significant and within their standard error limits and no variance non-stationarity was present. When the OPR was added to the model, an additional moving average component was needed. Table 11 below describe the results.

Table 11: Parameter Estimates for Reported Unlawful Entry – Dwelling Offences

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
MA1	.35 (.13)	2.73	.01
SAR1	-.48 (.12)	-3.92	.00
Post-intervention			
MA1	.25 (.10)	2.45	.02
MA2	.25 (.10)	2.46	.02
SAR1	-.50 (.09)	-5.52	.00
OPR	-435.6 (140.52)	-3.10	.00
Model-fitting information			
Akaike's Information Criterion			1273.05
Schwarz's Bayesian Criterion			1283.27
Likelihood ratio test			-632.53
Residual variance			35662.29
Standard error			188.84

As Table 11 shows, the introduction of OPRs was associated with a statistically significant decrease in unlawful entries into dwellings. This finding is consistent with Chilvers and Weatherburn's (2004) evaluation of the New South Wales equivalent of OPRs in Queensland and suggests that a large proportion of the decline in crime in Queensland is attributable to more effective policing via the OPR process for dealing with unlawful entry problems. We explore in more detail this finding in our second stage analysis described later in this report. Figure Two below shows the forecasted versus actual reported unlawful entries.

Figure 2: Forecasted versus Actual Reported Unlawful Entry of Dwellings



As Figure Two shows, had OPRs not been introduced across the State of Queensland in early 2001, we would have likely seen a steady, seasonally-based increase in unlawful entries. Indeed, by June 2004, the actual number of unlawful entries was 2,429. Without the introduction of OPRs, we could have expected to see the number of unlawful entries to be almost double the actual figure, ceteris paribus. Based on our analysis, we find that the introduction of OPRs resulted in a "savings" of about $870,000 in the state crime cost of residential burglaries.

Unlawful Entry – Other Premises

As with the other crime categories we conducted a time series analysis of the impact of OPRs on unlawful entry of "other premises" (including shops and other commercial or industrial buildings). Inspection of the pre-OPR time series observations did not appear to reveal a linear or seasonal trend. The ACF/PACF pattern was suggestive of an autoregressive component with positive spikes at ACF lag (1), (2), (3), and a negative spike at ACF lag (16). The largest PACF spike occurred at lag (1). An ARIMA (1,1,0) model was specified and the residuals of this model were non-significant and within their standard error limits. The addition of the post-OPR observations required the model to be adjusted to an ARIMA (2,1,0). All residuals were non-significant and within their standard error limits. Table 12 describes our results. As Table 12 shows, the introduction of OPRs was associated with a statistically significant decrease in reported unlawful entry offences into other premises (e.g. commercial establishments). We estimate the statewide crime “savings” that can be directly attributable to the introduction of OPRs to be about $1,233,000. That is, if the OPRs had NOT been introduced, then the cost of crime to Queensland would have been $1.2 million more in crimes of unlawful entry to commercial/business premises. This finding suggests that the problem oriented policing efforts of police in the area of dealing with unlawful entries is likely to be using tactics that are particularly important.

We note, however, that there was a decline in unlawful entries throughout most of the states in Australia, starting at about the same time that the OPRs were introduced into Queensland (see Appendix C). This is a major confounding factor that we cannot directly answer in the present analysis. Notwithstanding the Australia-wide trends in this category of crime (see Appendix C) that somewhat taint the strong findings that we show in our ARIMA analysis, we suggest that more research needs to be undertaken to understand the drop in crime in Australia, within the context of Australian states introducing COMPSTAT-like initiatives. Australian-wide, state-by-state analysis of COMPSTAT-like programs, much like what we have undertaken for Queensland, will help to understand the context of the crime drop in Australia and the extent that COMPSTAT-like programs have contributed to this decline.

Table 12: Parameter Estimates for Reported Unlawful Entry into Other Premises

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
AR1	-.47 (.10)	-4.46	.00
Post-intervention			
AR1	-.62 (.10)	-6.38	.00
AR2	-.22 (.10)	-2.31	.02
OPR	-274 (138.11)	-1.99	.049
Model-fitting information			
Akaike's Information Criterion			1399.94
Schwarz's Bayesian Criterion			1407.96
Likelihood ratio test			-696.97
Residual variance			27283.67
Standard error			165.18

Breach Domestic Violence (DV) Orders

The pre-OPR time series observations revealed an increasing linear trend and seasonality, with peaks in October to January of each year. After regular and seasonal differencing, the ACF/PACF pattern displayed a negative spike at ACF lag (1), indicative of a moving average process. An ARIMA $(0,1,1)(0,1,0)_{12}$ model for the pre-OPR time series possessed residuals that were non-significant and within their standard error limits. The model including the post-OPR observations required specification of a seasonal autoregressive component for its residuals to approximate 'white noise'. Table 13 describes the results. The results showed that the introduction of OPRs was associated with a non-significant increase in reported breaches of domestic violence orders. We expect this insignificant increase was largely due to efforts within the police department to emphasize the importance of charging people for breaches of DV orders (Superintendent Savage, personal correspondence, 11th May, 2005).

Table 13: Parameter Estimates for Reported Breach DV Orders

Parameter	Estimate (SE)	T-ratio	P-value
Pre-intervention			
MA1	.81 (.08)	9.50	.00
Post-intervention			
MA1	.81 (.06)	12.93	.00
SAR1	-.56 (.10)	-5.40	.00
OPR	8.81 (24.7)	.36	.72
Model-fitting information			
Akaike's Information Criterion			1024.91
Schwarz's Bayesian Criterion			1032.57
Likelihood ratio test			-509.45
Residual variance			2589.41
Standard error			50.89

Summary of Stage One Analysis

In our first stage analysis reported above, ARIMA interrupted time series analysis was used to assess the impact of OPRs on reported offences in Queensland. Using crime data spanning a 10-year period (1995 to 2004 inclusive), our results show that the introduction of OPRs contributed to a statistically significant reduction in total reported offences. We found that the introduction of OPRs prevented around 972 crimes, saving the state approximately $2,773,675[8]. Specifically, OPRs were associated with a significant reduction in unlawful entry offences (unlawful entries into dwellings and other properties). Serious assaults, common assaults, sexual offences, armed robberies, unarmed robberies, and unlawful use of motor vehicle offences all exhibited a non-significant decreases associated with the implementation of OPRs.

While not all of the declines in crime that we observed in our time series models emerged as statistically significant findings, they do hold some practical

[8] This figure is a conservative estimate given that the information on the costs of some types of crimes was unavailable.

significance. From the outset, we assumed that there could be four possible OPR outcomes: First, reported offences may have been increasing prior to OPRs and then continued to increase despite the introduction of OPRs. In this scenario, we would conclude that OPR were ineffective in making any type of impact on crime in Queensland. A second outcome could have been that reported offences may have been increasing and then stabilised in the post-OPR time period (i.e., a levelling off effect which would not emerge as a significant reduction). In this scenario, we would conclude that the OPRs were successful in harnessing the trend towards a rise in crime, but failed turn the trend around. A third outcome could have been that reported offences may have been either stable or slightly increasing in the period prior to the introduction of OPRs and then exhibited a non-significant decrease associated with the introduction of OPRs. In this case, we would have concluded that the OPRs were a contributor to the crime reduction, yet not especially important. Indeed, in this scenario other factors (such as demographic, income, employment) were likely to be the more important factors contributing to the crime reductions that OPRs. This is the line of argument described by Eck and Maguire (2000). The fourth possible outcome that we looked for in our statewide examination of the impact of OPRs in Queensland was that reported offences may have been initially increasing and then exhibited a significant decrease associated with OPRs. In this scenario, we would conclude that the introduction of OPRs was an important factor contributing to the crime drop across Queensland. We suggest that the last three types of outcomes to be indicative of “success” regardless of statistical significance, particularly considering that population growth across the State of Queensland in the last three years follows a steadily increasing pattern from around 58,000 people per year to 81,000 people from 2003 to 2004 (Queensland Government, 2005).

The question of whether OPRs are a cost-effective intervention may be addressed by weighing the costs of OPRs against the savings attributable to reduced crime. The cost of OPRs for 2004/2005 included salaries amounting to $476,500 and travel expenses ($40,000) while the equipment costs (e.g., computers, projectors) amount to around $62,000. This brings the total cost of OPRs since their implementation to approximately $1,611,500. When we weighed these operational costs of OPRs against the savings of reduced crime ($2,773,675), the introduction of OPRs appears to have been cost-effective, resulting in an overall saving of $1,162,175.

Importantly, we note the Queensland crime trends in context to the rest of Australia. Appendix C includes graphs of the reported crime trends by State and for the Australian average. We note, for instance, that Australia reported drops in unlawful entries from about 2001 onwards, confounding somewhat our OPR impact evaluation. There are many possible explanations for this drop: perhaps COMPSTAT-like programs introduced across Australia did in fact contribute to the crime drop? Perhaps the heroin drought reduced the rate of unlawful entries? Perhaps the economic factors in Australia around the same time that COMPSTAT like programs were introduced were more important predictors of the drop in crime. All of these explanatory factors are explored in detail in the US context (see Blumstein & Wallman, 2000). Overall, we suggest that our results show that OPRs in Queensland are an important factor in reducing crime, particularly unlawful entires, yet we are unable to rule out the importance of some of the other explanations that have accompanied crime drops elsewhere in the world. As such, we suggest that there is a need for careful, state-by-state analysis of the introduction of COMPSTAT-like programs in the context of assessing economic, political and social trends in order to understand the role of COMPSTAT in contributing to the drop in crime in Australia.

STAGE TWO ANALYSIS: DISTRICT VARIATIONS IN OPR IMPACT

The results of our time series analysis using the state-wide data suggests that the introduction of OPRs in Queensland contributed in important ways to the decline in crime in the state. However, our first stage analysis did not control for other factors that may have influenced the number (or rate) of reported offences. For example, a tradition of criminological research spanning many decades shows that a range of socio-political-economic factors such as population growth, socioeconomic disadvantage, employment, urbanisation, industrialization, demographic transformations (Cancino, 2005; Eck & Maguire, 2000) are important variables that explain significant portions of crime fluctuations over time. We expect that these socio-political-economic factors would influence crime trends in Queensland in the late 1990s and early 2000s. Further, we expect that important differences between the 29 police districts would contextualise our statewide research findings and provide insight into some of the nuances of how OPRs contributed to the overall crime reductions in Queensland. That is, we suspect that the statewide results described in our Stage One analysis may have obscured important district-level variations in OPR implementation[9].

[9] It is important to recognise that the structure of police forces is inherently 'nested' in that police divisions are subsumed under police districts. In a proposed follow-up project we seek funds to explore the spatial and temporal variations in the impact of OPRs at the Divisional level of analysis. There are 295 police divisions throughout Queensland. Our preliminary spatial mapping of the divisional level data (n = 295 divisions), reveal that even *within* police districts there is variation in the impact of OPRs on crime outcomes. We hypothesize that this within-District variation is a function of (a) variation in the way that the principals of OPRs have penetrated down to the divisional level of command (b) social structural variations within Districts and (c) the uniqueness of crime problems facing different divisions. Our follow-up funding request is to explore the divisional level variations in crime over time. The OPR intervention will be just one explanatory variable. We also expect that social structural factors (measured via census data) and unique crime problem profiles will explain some of these

The second stage of our analysis involved the application of mixed model statistical techniques to analyse the district-by-district variations in the longitudinal time series data while controlling for socio-structural variables. Our time series analysis helped to assess the effectiveness of OPRs across all of Queensland. From the outset, however, we thought it likely that OPR effectiveness would vary depending upon the socio-political-economic characteristics of each district and the way that OPRs might have been implemented differently across each of the 29 police districts throughout Queensland. As such, in our second stage analysis, the 29 police districts are considered "nested" units of analysis within the State of Queensland. We account for variations in the districts according to their geographical attributes (e.g., size), socio-demographic factors (e.g., SES, racial composition), as well as policing variables (e.g., district size, leadership). Rather than simply ignoring these potential influences, our mixed model analysis incorporates these factors in one overall model to provide a more accurate assessment of the effects of OPRs on reported offences.

The independent variable is OPR implementation while the dependent variables consist of the various crime types described in Appendix B. The first level considered in the analysis is that of **time** (108 observation points). The second level of analysis is the **district** level (N = 29 police districts). Each district also has its associated **structural covariates** (including population size, socio-economic status, the proportion of people renting and overseas dwellers). It is therefore possible to assess the relationship between these structural covariates and the effect of OPRs across the 29 police districts in Queensland.

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divisional level variations. We would use group-based trajectory analysis to uncover distinctive developmental trends in crime problems across our population of 295 divisions.

Data

Table 14 below provides a synopsis of the sources and construction of our data used in our Stage Two analysis. As this table shows, our data comprised crime rates for 13 crime types (See Appendix B for a description of the crime categories) across the 29 Queensland Police districts measured over 108 months[10]. The dependent variables included in our multi-level models are these crime figures converted to a rate per 100,000 people.

A seasonal indicator variable was created to account for seasonal variations in crime rates, representing Summer (December to February), Autumn (March to May), Winter (June to August), and Spring (September to November).

Moran's Index (MI) is incorporated as a measure of spatial dependency. This measure has been previously utilised in a similar fashion in the criminological field (Baller, Anselin, Messner, Deane, & Hawkins, 2001; Griffiths & Chavez, 2004; Kubrin & Herting, 2003). We point out that the coefficients relating to this variable are not used for interpretation. Rather, they are present in the models to account for spatial dependency between districts.

Our models also included an ABS census construct called "social disadvantage." This index is the combination of several ABS indices containing overlapping information. To avoid problems with multi-collinearity the demographic variables entering the model are restricted to the index of relative socioeconomic disadvantage (DIS), the number of people renting in each district (RENTING), and the number of

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[10] We note that the data across the 29 police districts were complicated by the changes in district boundaries during the ten-year study period. Specifically, the Metropolitan North Region had undergone massive boundary changes over the 10-year period. Prior to July, 1996 this region consisted of two major districts. Between July, 1996 and July 2002, the two districts were divided into 9 "clusters" and these clusters were split into the four current districts after July 2002. It was necessary to estimate the crimes in the four current districts by overlaying QPS boundary files with land parcel area maps, identifying unique areas corresponding to the four districts over time, and mapping the reported offences prior to 2002 to the current district boundaries.

people from overseas (OVERSEA). The latter two variables were standardised to rates per 100,000 using population figures.

Seven senior members of the QPS rated the majority of the district officers on leadership characteristics using14 items adapted from the Multifactor Leadership Questionnaire (MLQ; Bass & Aviolo, 1995). The MLQ has been found to be a reliable and valid measure of optimal leadership characteristics (see, for example, Antonakis, Aviolo, & Sivasubramaniam, 2003). For ease of analysis, district leadership scores were dichotomised: high and medium (1) versus low (0). Additionally, there were missing leadership ratings typically occurring prior to April, 1999. These ratings were replaced with the median scores based upon leadership characteristics of each district[11]. Table 14 provides a summary of the variables used in the Stage Two analysis.

Table 14: Summary of Stage Two Variables

Variable	Measurement Details	Source
Crime rates per 100,000 persons	Continuous, interval level variable. See Appendix B for category details	QPS
Leadership	Dichotomous variable. High/medium versus Low. Scale range (0, 1)	Bass & Aviolo (1995); QPS senior management survey
District population	Continuous, interval level variable	ABS
Level of disadvantage	Continuous, interval level variable	ABS
Overseas dwellers	Continuous, interval level variable	ABS
Renting dwellers	Continuous, interval level variable	ABS
Moran's I measure of spatial autocorrelation	Continuous, interval level variable	GeoDa (Anselin, 2005)

[11] We initially tried to use the number of cleared offences in each district as predictors of leadership ratings in a discriminant function analysis to impute missing values. However, cleared offences produced poor discrimination and we opted for the median approach instead.

Transformations of the dependent variables (natural log and square root) were used to satisfy assumptions of the models used where appropriate. Generally these transformations stabilised variability and/or induced approximate normality in the model error terms. Where transformations failed to produce the desired effect, a more complex and computationally intensive class of model was used. The transformations used for each of the different crime categories are briefly discussed in the following section. Results should be interpreted on the scale of the transformed response variable. Given that the transformations are monotonic and increasing, and 1 to 1 ("onto") over the range of the response, this poses no significant problems in the interpretability of the transformed variable.

The Mixed Model Analytic Approach

Table 15 describes the descriptive statistics for the variables included in our Stage Two models. Not surprisingly, Table 15 shows that there is considerable variation in the social structural and crime rates across the 29 police districts in Queensland. Given the variation in crime and social structural characteristics, we expect to uncover important differences between the districts in the impact of OPRs on the different categories of crime. These findings are important to help us understand the role of introducing OPRs in understanding the overall crime drop in Queensland. For example, was the crime drop equal across all the districts? If it was, then we would expect that our Stage One analysis would be compromised and that the Australian-wide drop in crime to be attributable more so to other factors (such as social structural change) than to the introduction of OPRs. Alternatively, since we know there is considerable variation in crime and social structural characteristics between the districts in Queensland, if we find that introduction of OPRs have a variable (rather than a constant) impact on crime, then we are getting closer to understanding the unique contribution that OPRs have had on the crime drop.

Table 15: Descriptive Statistics for Stage Two Analysis (N = 29)

Variable	Mean (SD)	Median	Range
Offence Types			
Total Offences	352.4 (304.7)	255	4 – 1565
Homicide	0.55 (0.99)	0	0 – 15
Dangerous Driving	0.25 (0.64)	0	0 – 5
Unlawful Use of MV	50.17 (61.96)	23	0 – 369
Serious Assault	30.21 (24.04)	24	0 – 138
Common Assault	20.3 (15.68)	17	0 – 104
Sexual Offences	16.56 (27.44)	11	0 – 830
Armed Robbery	2.96 (4.12)	1	0 – 30
Unarmed Robbery	3.19 (4.13)	2	0 – 26
Ill Treatment of Children	1.52 (4.77)	0	0 – 85
Menacing Person Offences	7.78 (7.13)	6	0 – 47
UE – Dwelling	116.8 (122.16)	72	0 – 677
UE – Other Premises	83.51 (68.26)	67.5	0 – 436
Breach DV Order	16.4 (15.79)	12	0 – 136
Socio-demographics			
Population per District	119200 (83925.65)	121800	9828 – 393500
Overseas	19860 (20050.6)	11980	488 – 93790
Renting	12730 (10255.17)	11650	858 – 53440
Disadvantage	991.2 (41.97)	988.3	893.4 - 1129

Our Stage Two data analysis was specifically designed to explore variations in district contributions to the overall reductions in crime across the State of Queensland. To answer our research question we needed to use specialised and reasonably complex statistical modelling techniques. Specifically, both within-and between-district variability in crime rates needed to be taken into account due to the hierarchical nature of the data. Further, crime rates within each district are time series, which raises the possibility of temporal autocorrelation. In addition, districts in close spatial proximity to each other might be expected to display similar crime patterns through time, or spatial autocorrelation. Finally, the response variables (crime rates) are in fact counts. Unless a suitable transformation of the response can be found a model which assumes a continuous response will be inappropriate.

Therefore, two (related) classes of model were used in the following analyses: the linear mixed effects model (LMM) and the generalised linear mixed effects model (GLMM). Both allow the modelling of within- and between-district variability and spatial autocorrelation (via the inclusion of an appropriate spatial dependency variable – Moran's Index in this case). Currently, only the former (the linear mixed effects model) models temporal autocorrelation. LMMs require a continuous and normally distributed response – these are used when the crime rate figures can be transformed to approximate normality. GLMMs are used when the response variable is non-normal (e.g., Poisson) or cannot be made normal via transformation.

The general form of a LMM is

$$y_{ij} = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p + b_{i0} + b_{i1} Z_{i1} + \ldots + b_{iq} Z_{iq} + \varepsilon_{ij}, \quad i = 1, \ldots, m, \quad j = 1, \ldots, n_i, \tag{0.1}$$

where y_{ij} denotes the jth response (crime rate) on the ith district (so that $m = 29$ and $n_i = 108$), β_k, $k = 0,1,\ldots,p,$ represent the (fixed) effects of covariates X_k (X_0 is a unit vector, and thus is omitted from (0.1)), b_{ik}, $k = 0,1,\ldots,p,$ are district—specific random effects corresponding to covariates Z_{ik} (similar comments as for X_0 apply to Z_{i0}), and ε_{ij} denote the error terms. The error terms are assumed independent and identically distributed as normal random variables with mean 0 and variance σ_ε^2 (note however that the assumption of independence can be overcome by allowing the error terms to have a multivariate normal distribution with mean vector 0 and variance—covariance σ_ε^2 R, where R is a symmetric and patterned correlation matrix). Similarly, the random effect coefficients $\mathbf{b}_i$ are assumed multivariate normal with mean vector 0 and variance—covariance matrix Σ. Random effects are assumed independent between districts.

Fixed effects are interpreted as population effects of the corresponding covariate whereas random effects are interpreted as the district – specific deviation from the population induced by the corresponding covariate. Between district variations in the response is represented by Σ. Within district variability is represented by σ_{ε}^{2}. The general expression for a GLMM is slightly more complicated than that shown in (0.1). For the GLMM a function, g, of the expected value of the response, μ_{ij}, is related to a linear combination of the covariates (also known as the linear predictor) via

$$g\left(\mu_{ij}\right)=\beta_{0}+\beta_{1}X_{1}+\ldots+\beta_{p}X_{p}+b_{i0}+b_{i1}Z_{i1}+\ldots+b_{iq}Z_{iq},\quad i=1,\ldots,m,\quad j=1,\ldots,n_{i}, \tag{0.2}$$

where symbols are as defined previously and g(.) denotes the link function. In addition, it is assumed that, given the random effects, the distribution of the response is a member of the exponential family. For the cases considered here the distribution of the response is assumed to be Poisson, with a probability density function (pdf).

$$P\left(Y_{ij}=y_{ij}\mid\mathbf{b}_{i}\right)=\frac{e^{-\mu}\mu^{y_{ij}}}{y_{ij}\,!},\quad y_{ij}=0,1,2,3,\ldots\,.$$

In this expression μ_{ij} represents the mean of the response and is physically interpreted as the rate at which crimes occur per month. Generally the link function chosen is the natural logarithm which, among other things, allows fixed effects parameters to be interpreted as the effect of the particular covariate on the log of the monthly crime rate.

Model Fitting

The general approach taken to modelling the data and producing the results shown in the following section was as follows: A LMM was initially fit to the data and an assessment of the model fit undertaken using graphical and other techniques (such as the Box-Cox transformation). Based on this assessment, a suitable transformation of the response variable was selected to achieve normality and constant error variability. If such a transformation was found, the LMM was refit and reassessed and final model estimates presented. If no such transformation could be found a GLMM as described above was fit to the data, assessed, and results presented.

Under the LMM, auto-correlated error terms (an AR(1) model) are included to account for any dependencies left in the response. Assessment of whether this added complexity is warranted is achieved via examination of a likelihood ratio test. The AR(1) coefficient is only included in those models where the coefficient is significant. Covariates included in the random effects (i.e., those variables thought to vary between districts) include an intercept (a measure of each district's intrinsic differences), "Time" (to allow for the fact that different districts crimes have different progressions through time) and "OPR" (to allow for differences in the efficacy of the OPR in each district). Note that numerical and computational difficulties when fitting models means that in some cases only a subset of these variables appear in the random effects. These are shown graphically in the accompanying figures below, and are ordered by district code from best to worst in Appendix D. Note that when OPR is included in the random effects only, the ranking based on OPR is presented. In addition to fixed effects estimates, random effects predictions are also obtained to assess where OPRs had the biggest impact.

Results

Complete results for the models created for each crime type are presented in Appendix D. The following discussion of results describes and interprets only those effects significant at the 0.1 level.

Total Reported Offences

The natural logarithmic transformation was used for these data and an LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.51) and OPR (sd = 0.098) when compared to the within-district variability (sd = 0.199). This means that there are considerable variations in the starting crime rates across the 29 police districts in Queensland, as we would expect to be the case.

The error term AR(1) parameter estimate is 0.326. A significant positive Time-OPR interaction ($p = 0.0022$) indicates that, compared to pre-OPR, the monthly post-OPR log overall crime rate has increased by, on average, 0.007. This outcome is complicated by two features of the model: first, the fact that the direct relationship of OPRs on the total reported crime rate is negative (-.565) suggesting a decline in crime consistent with the time series results but second, the time variable is positive (.007) suggesting that crime is rising over time. Note also the significant, negative Time squared effect, indicating that log overall crime rates are decreasing with time. This effect, combined with the Time-OPR effect might be masking what is really going on with the OPR. In short, our time series results, along with the negative quadratic time variable suggests the importance of the implementation of OPRs in mitigating increases in crime across some of the key districts in Queensland.

When we examine the specific districts that contributed to the decline in total reported crime, we gain further understanding of the influence of OPRs (see Figure 3). We know that two Districts in particular (A and B[12]) performed the best throughout the state in terms of reducing crime. Both Districts A and B are urban areas: one regional and the other city. District A's decline in crime was driven by reductions in break and enter, unarmed robbery, dangerous driving and sexual offences. In contrast, District B's decline in crime was driven by reducing assaults (common and serious), offences against the person, unarmed robbery, unlawful use and break, enter and steal.

When we look at the flip side of the overall reductions in crime as a result of OPRs, we find that some of the Districts with major urbanisation and in-migration experiences over the last ten years (especially Districts C, D and E) confounded the declines in crime, by consistently posting increases in crime. In District C, for example, the total crime rate increase was driven by significant increases in unarmed robbery and common assault. In District E, increases in crime were driven by unlawful use of motor vehicles, break and enter and unarmed robbery.

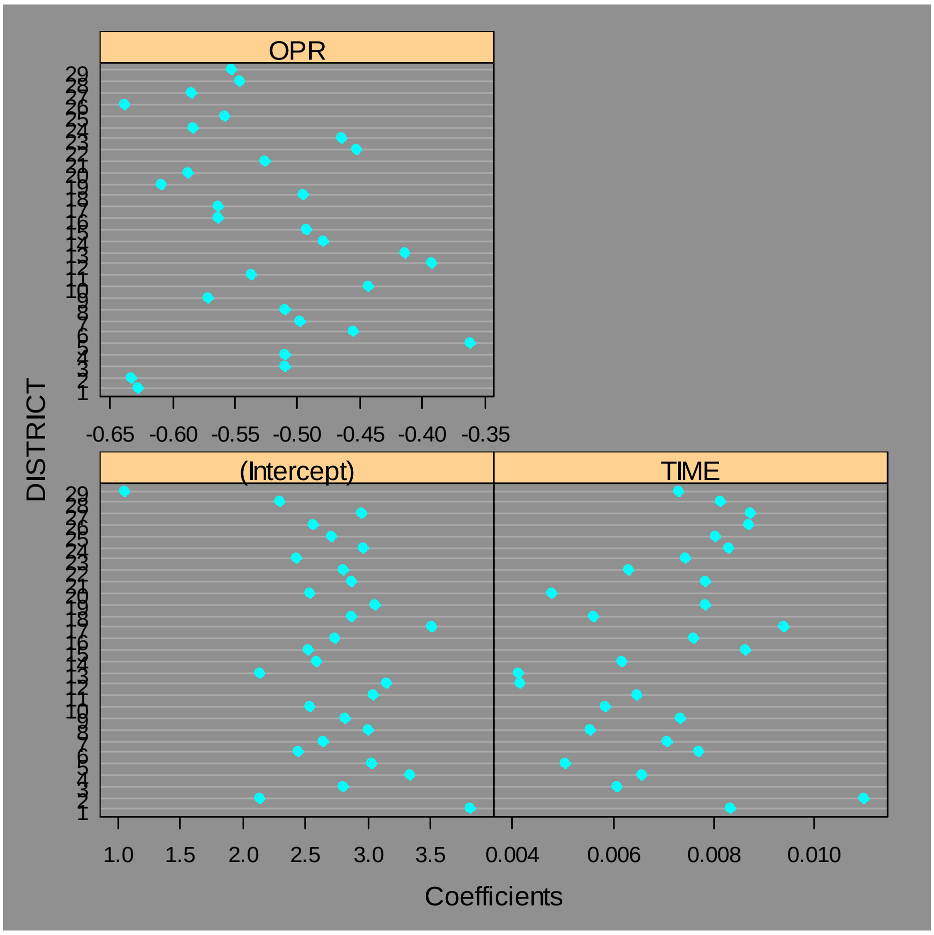
A positive significant disadvantage effect ($p < 0.0001$) indicates that, as disadvantage increases by 1 unit, the log rate of overall crime increases by, on average, 0.003, suggesting the importance of the amount of social disadvantage in a police district has an impact on rising crime rates. There is some evidence of seasonality for these data.

Overall, our mixed model analysis of the impact of OPRs on total reported crime suggests that there a major differences between the districts, that some of the districts are driving the overall statewide crime reductions, whilst others are

[12] All references to the Districts, both the numeric code included in Appendix D and the alpha code (A through G) included in the text are used to protect the districts from identification. We note too that the alpha code does not match up to the numeric code.

confounding the positive effects of implementation of OPRs in Queensland. The issue of social disadvantage certainly plays a part in understanding district variations in crime, but not as an overall superior predictor to the OPRs. Our total crime model also shows marginal influences of effective leadership, albeit the leadership issue is not a significant predictor. We discuss the policy importance of these variations in OPR across the districts and the unique district contributions to crime increases and decreases in the concluding section of this report. The random effects for this model are shown in Figure Three below.

Figure 3: Random Effects for Total Reported Offences



Homicide-Related Offences

A transformation of the response was unsuccessful and a Poisson GLMM was therefore fit. Fitting failed when OPR and Time were included in the random effects. These results are therefore based on a random intercept model. Significant between-district variability was observed (standard deviation, sd = 0.325). The Time/OPR interaction term was significant at the 0.1 level (p-value = 0.0714) and was negative, indicating that as time advances the OPR decreases the log rate of crime by, on average, 0.01 per month when compared to those times without OPR, across Queensland. There was also a significant negative effect of socio-economic disadvantage (DIS) ($p = 0.0056$). This indicates that as socio-economic disadvantage increases by 1 unit the log of crime rates decreases by, on average, 0.004. Similarly, rent was significant and positive ($p = 0.002$) indicating that as the ratio of renters to population increases by 1 unit, the log of homicide rates increases by, on average, 11.19. Both population and Moran's I are significant but neither should be interpreted as they are control variables only.

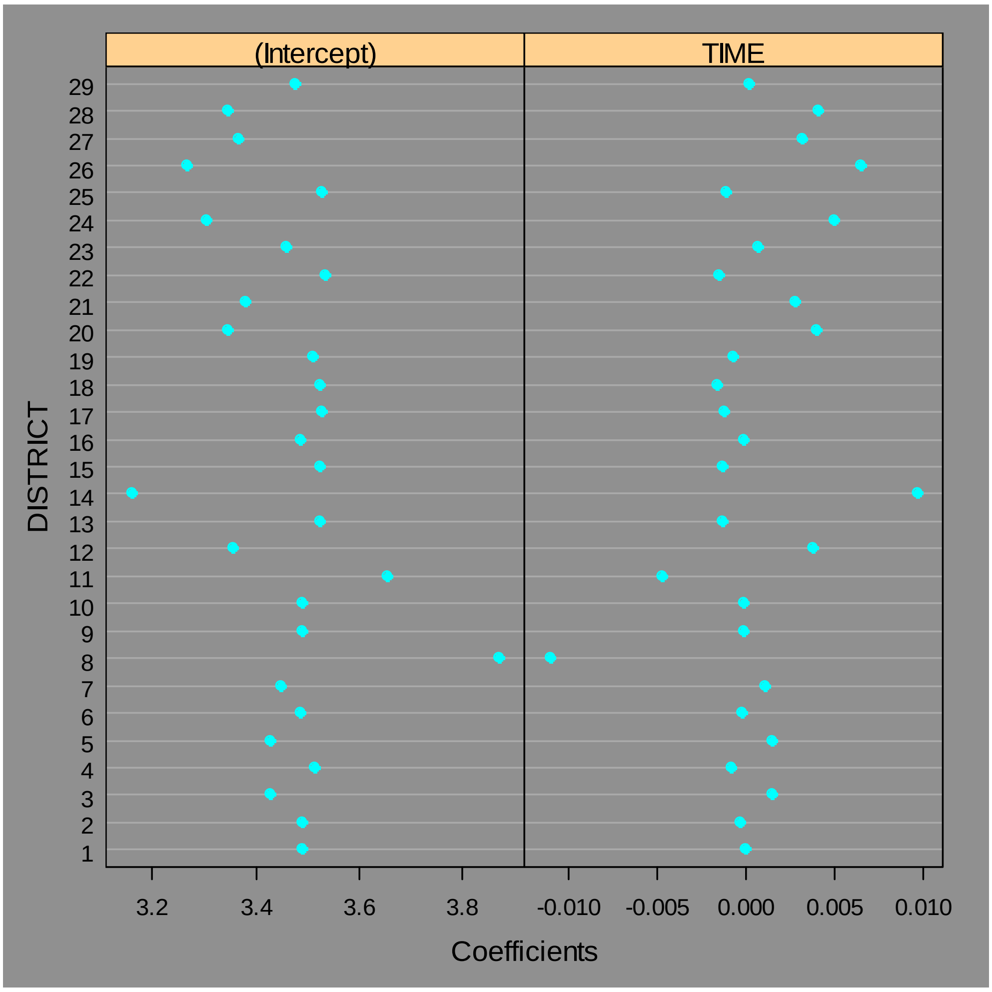
Dangerous Driving

A transformation of the response was unsuccessful and a Poisson GLMM was therefore fit. Fitting failed when OPR was included in the random effects[13]. These results are therefore based on a random intercept and Time model. There was significant between-district variability, particularly in the intercept (sd = 0.2). A significant negative effect of disadvantage ($p < 0.0001$) was observed and indicated that as disadvantage increases by 1 unit, the log of dangerous driving rates decreases by, on average, 0.006.

[13] There are a number of reasons why fitting might fail, including lack of convergence of the fitting algorithm and numerical underflow or overflow problems.

The only other significant effect of note is that of leadership (p = 0.0114). The coefficient indicates that, compared to poor leadership, good leadership *increases* the log dangerous driving rate by, on average, 0.254. This finding is potentially the result of traffic "blitzes" orchestrated by high performing district leaders, that, whilst effect at reducing crime in other categories, increased the reported rate of dangerous driving. The Intercept and Time random effects are shown in Figure Four below.

Figure 4: Random Effects for Reported Dangerous Driving Offences



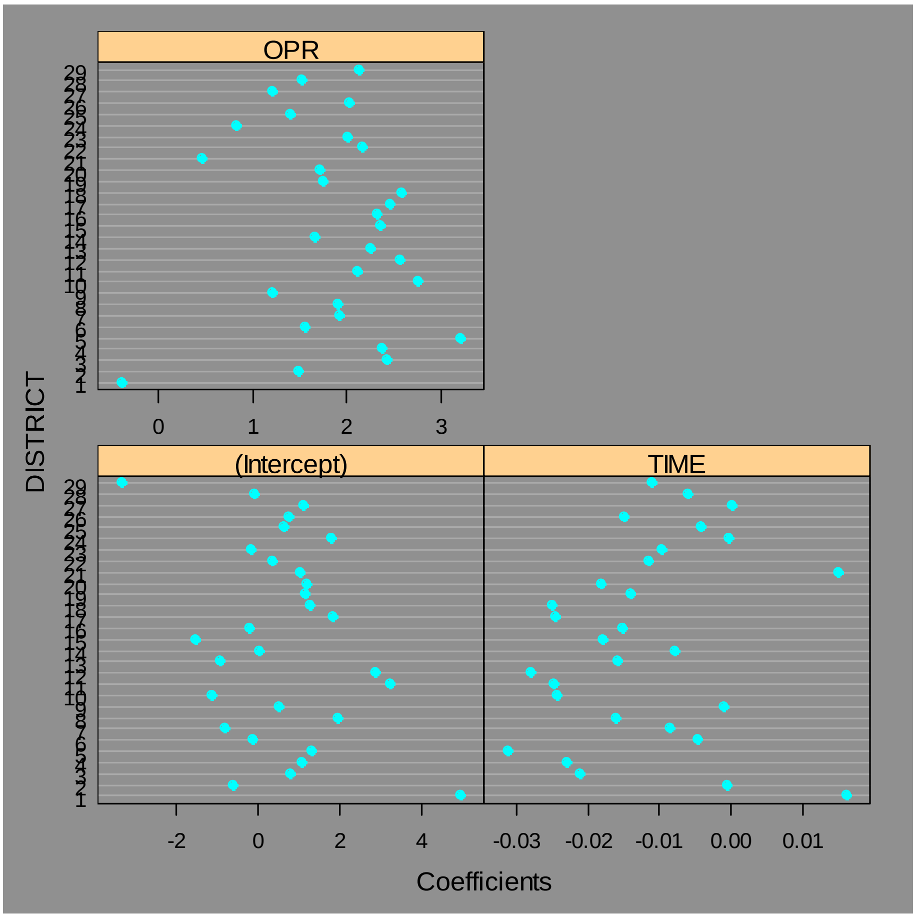
Unlawful use of Motor Vehicle Offences

The square root transformation was used for these data and a LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the square root scale. Significant between-district variability is observed, particularly for the intercept (sd = 1.63) and OPR (sd = 0.82) when compared to the within-district variability (sd = 1.06). The error term AR(1) parameter estimate is 0.210. A significant negative Time-OPR interaction (p = 0.0008) indicates that, compared to pre-OPR, the monthly post-OPR square root rate of unlawful motor vehicle use has reduced by, on average, 0.031. Again, this result is consistent with our time series findings. When we examine the characteristics of the between district variations we find an important nuance to the data. District G contributed significantly to the post-OPR decline in unlawful use of motor vehicles. This particular district had expended considerable resources in developing crime mapping technologies and working hard post OPR introduction on reducing unlawful use of motor vehicles in one particular shopping centre. This result suggests that very micro-level, problem-oriented policing interventions may have considerable impact not only on the district success in reducing crime, but could potentially spearhead the state-wide reductions when major hot spots are identified and dealt with. We explore this idea further in our concluding section.

A negative significant leadership effect (p = 0.0128) is found in this model indicating that, compared to low leadership, high leadership decreases the square root rate of unlawful motor vehicle use by, on average, 0.355. This is an important finding and one of the only models in our analysis that reveals the significance of strong leadership in reducing crime in the post OPR time period. After break and enter offences, unlawful use of motor-vehicle offences was an important crime type driving the overall crime rate of Queensland down in the post-OPR period. It is unclear, however, why it was that strong leadership did not seem to influence the post OPR reductions in break and enter.

There was also a positive significant effect of the proportion of overseas-born dwellers (p = 0.0044) indicating that as this proportion increases by 1 unit, the square root rate of unlawful motor vehicle use increases by, on average, 11.55. Note also the positive significant Time squared coefficient indicating that square root rates of these crime are increasing over time. Random effects from this model are shown in Figure Five below.

Figure 5: Random Effects for Reported Unlawful use of Motor Vehicle Offences

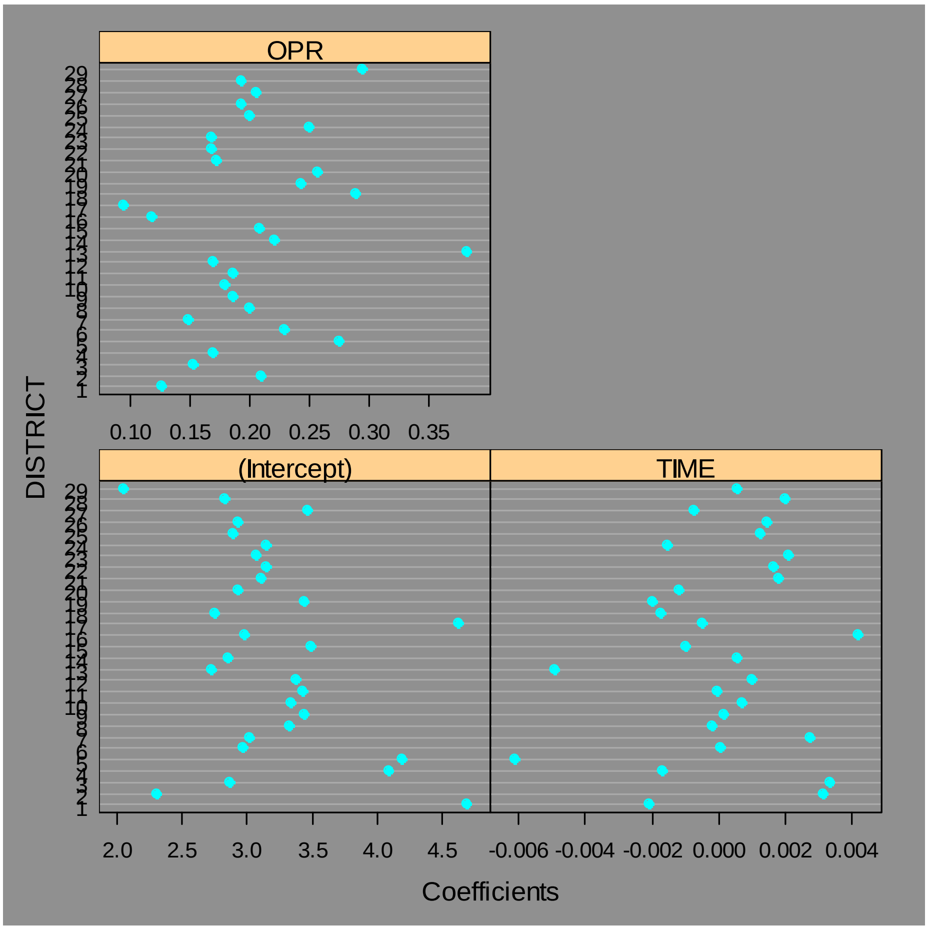


Serious Assault

The natural logarithmic transformation was used for these data and a LMM fit. An intercept, Time and OPR random effect term were included. No AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.604) when compared to the within-district variability (sd = 0.36). This suggests that unmeasured factors are potentially influencing the variations in district crime rates over time.

Both proportion renting and proportion overseas-born were significant at the 0.1 level (p = 0.09 and 0.06, respectively), but their effects are opposite: a unit increase in the proportion renting increases the log rate of serious assaults by, on average, 3.7 whereas a unit increase in the proportion of overseas-born dwellers decreases this rate by, on average, 2.39. When we examine the districts where OPRs are contributing to increases in serious assaults, we notice that one district is in outback Queensland and the other in coastal Queensland. Again, leadership cannot explain the variation, yet the significant seasonal component does help to explain the variation. Our model suggests that changes in serious assault rates are potentially the result of seasonal worker effects. This model's random effects are shown in Figure Six below.

Figure 6: Random Effects for Reported Serious Assaults

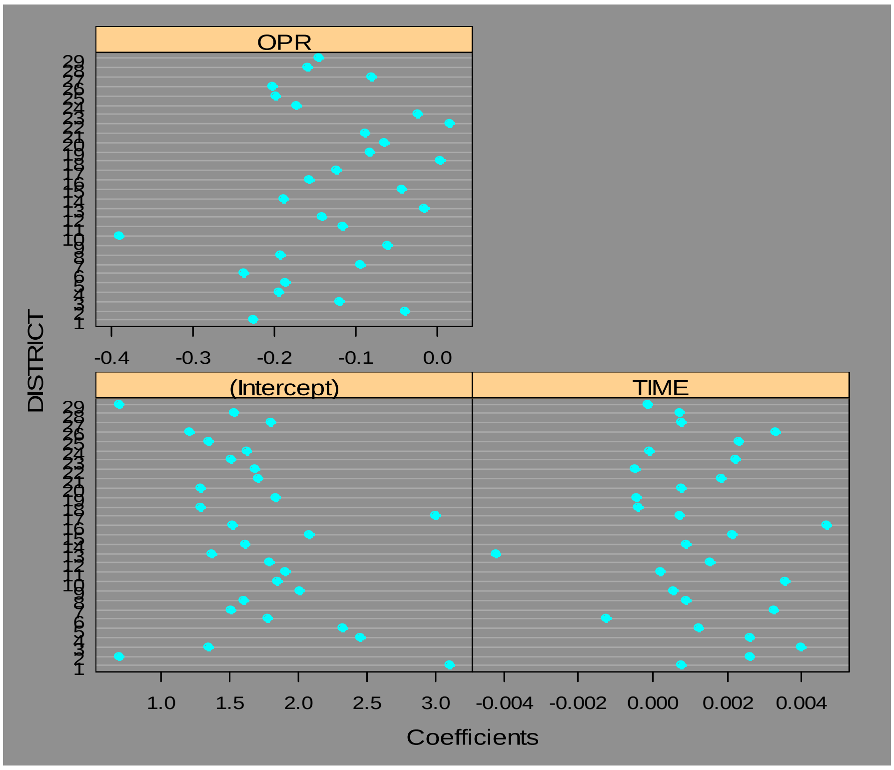


Common Assault

The natural logarithmic transformation was used for these data and a LMM fit. An intercept, Time and OPR random effect term were included. No AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.556) and OPR (sd = 0.132) when compared to the within-district variability (sd = 0.44). The only significant effect of note (besides a seasonality component) was that of Time (p = 0.086) at the 0.1 level. The Time coefficient indicated that as time increases by 1 month, the log rate of common assaults increases by, on average, 0.001. That is, common assault is gradually increasing over the period described by this data, and

OPR has no effect on this rise. Random effects for this model are shown in Figure Seven below.

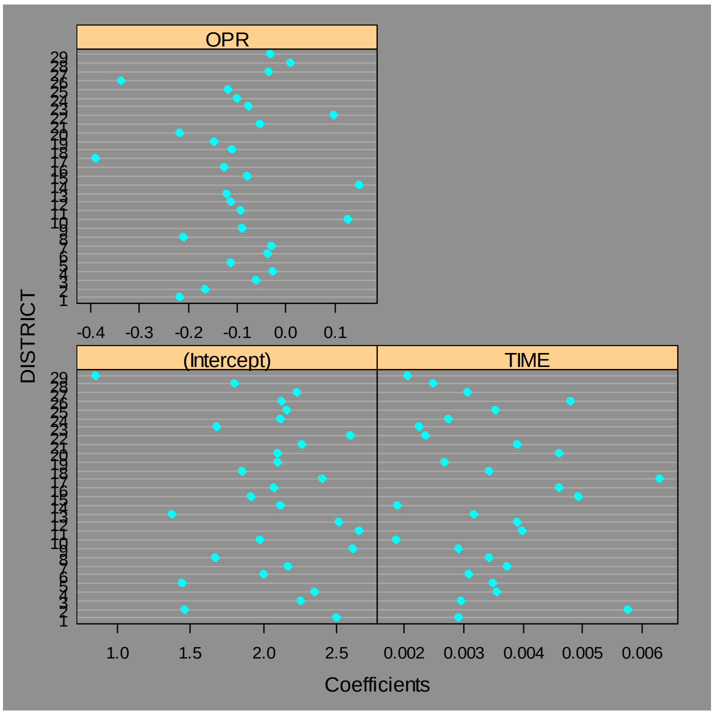
Figure 7: Random Effects for Reported Common Assaults



Sexual Offences

The natural logarithmic transformation was used for these data and a LMM fit. An intercept, Time and OPR random effect term were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.444) and OPR (sd = 0.200) when compared to the within-district variability (sd = 0.81). The autoregressive parameter estimate for the within district error terms was 0.038. The proportion renting was significant at the 0.1 level (p-value = 0.0514) with a positive coefficient indicating that as the proportion renting increases by 1 unit the log rate of sexual offences increases by, on average, 6.36. There was also a significant time effect (p = 0.005) indicating that the per month increase in log sexual offences rate increases by, on average, 0.003. Again, the time/OPR interaction effect was not significant. The random effects for this model are shown in Figure Eight below.

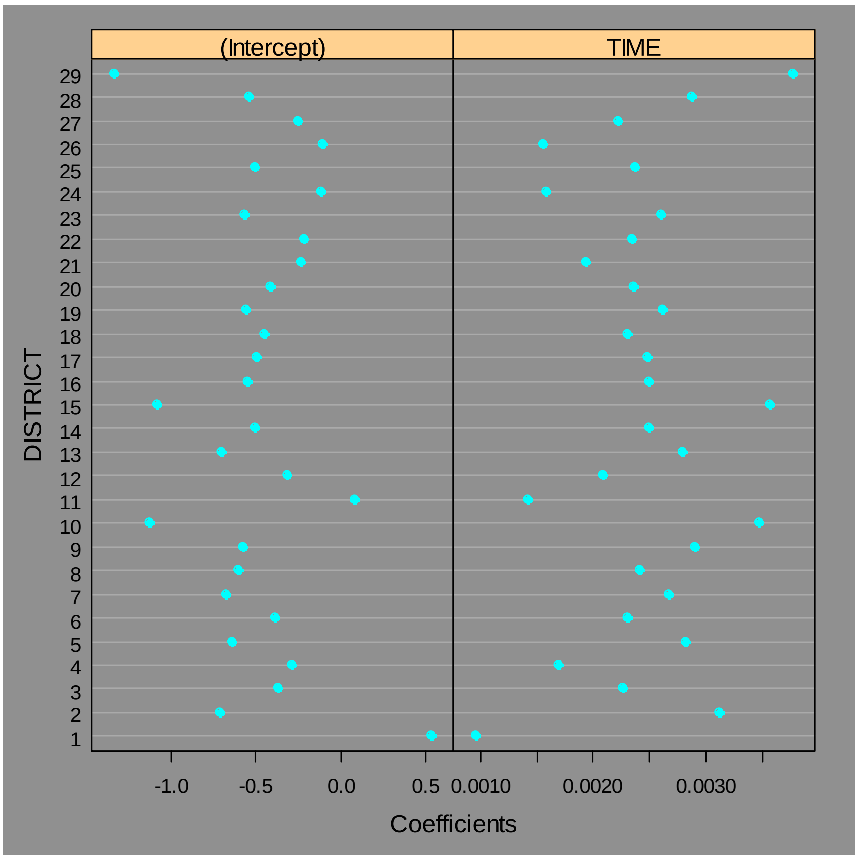
Figure 8: Random Effects for Reported Sexual Offences



Armed Robbery

The natural logarithmic transformation was used for these data and a LMM fit. Intercept and Time random effects terms were included – fitting failed when trying to include a random effect for OPR. No AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.37) when compared to the within-district variability (sd = 0.49). The proportions of those renting and overseas-born dwellers were both significant and positive (p = 0.026 and <0.0001, respectively). For renters, the coefficient indicated that as the proportion increases by 1 unit the log rate of armed robbery increases by, on average, 4.45. For overseas-born dwellers, the coefficient indicated that, as the proportion increases by 1 unit the log rate of armed robbery increases by, on average, 5.02. There was also a significant Time effect (p < 0.0001) indicating that, over the time period collected, the log rate of armed robbery is increasing by, on average, 0.002 per month. We note that the time/OPR variable is negative (suggesting a decline in armed robberies over time as a result of the introduction of OPRS), but the effect is not statistically significant (p=.25). Random effects for this model are shown in Figure Nine below.

Figure 9: Random Effects for Reported Armed Robberies

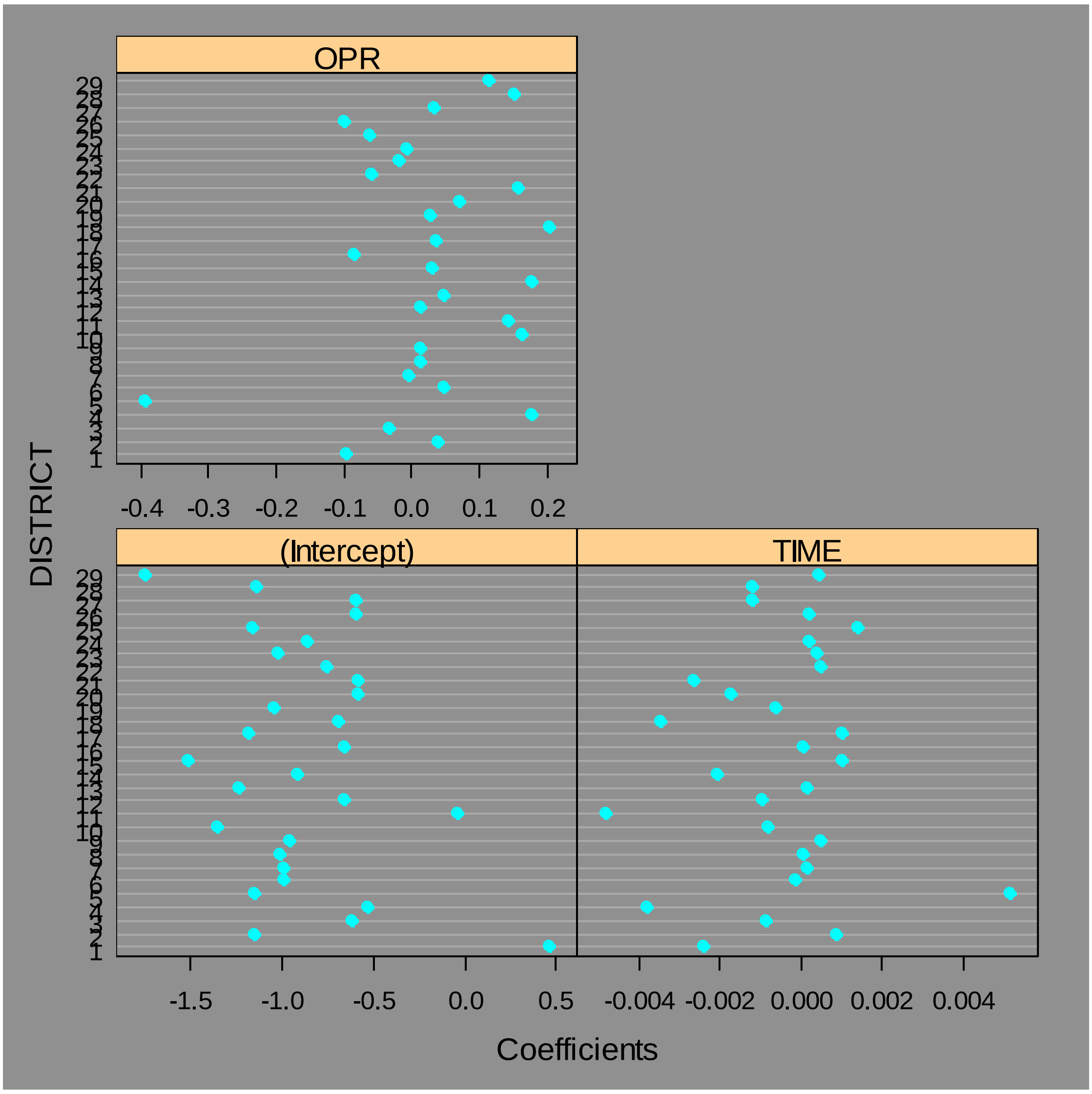


Unarmed Robbery

The natural logarithmic transformation was used for these data and a LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.45) and OPR (sd =

0.17) when compared to the within-district variability (sd = 0.51). The error term AR(1) parameter estimate is 0.045. The proportion renting and the proportion of overseas dwellers were the only two significant variables (p = 0.0001 and <0.0001, respectively). For renting, as the proportion increases by 1 unit the log rate of unarmed robbery increases by, on average, 8.4. For overseas-born dwellers, as the proportion increases by 1 unit the log rate of unarmed robbery increases by, on average, 4.5. Random effects for this model are shown in Figure 10 below.

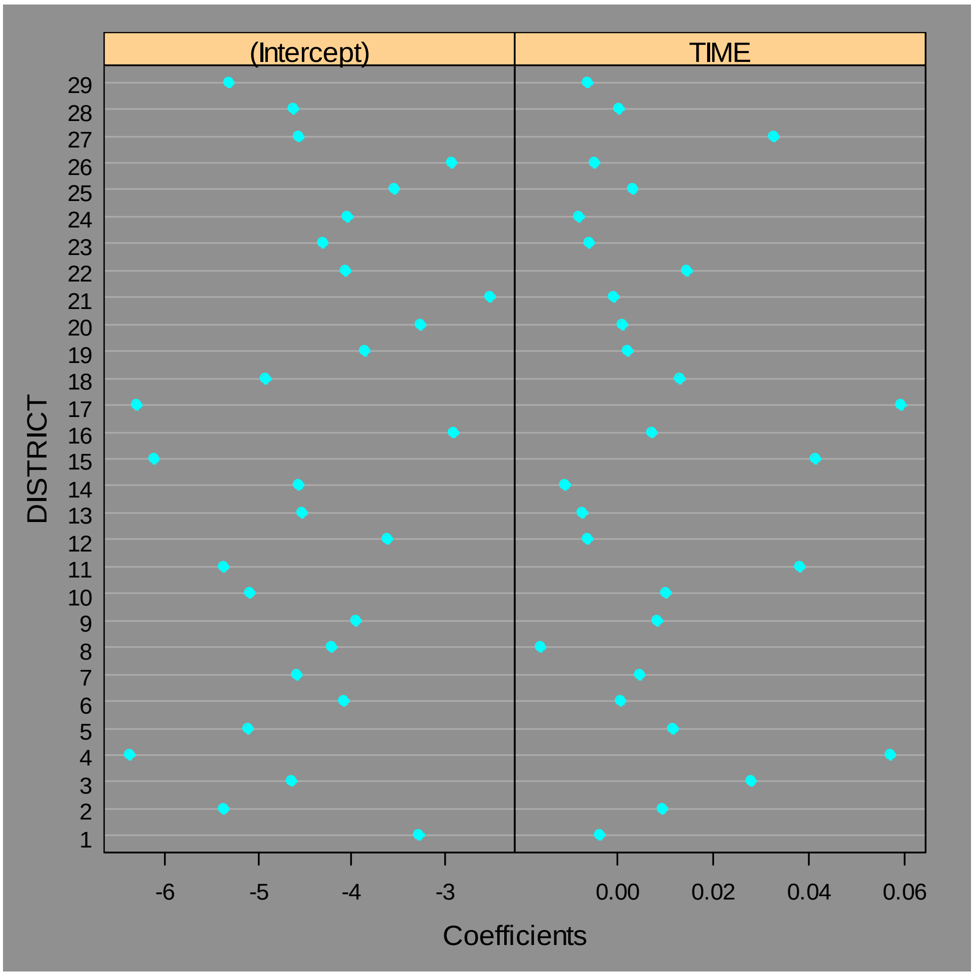
Figure 10: Random Effects for Reported Unarmed Robberies



Ill Treatment of Children

A transformation of the response was unsuccessful and a Poisson GLMM was therefore fit. Fitting failed when OPR was included in the random effects. These results are therefore based on a random intercept and Time model. Significant between-district variability was observed, particularly for the intercept (sd = 1.11) when compared to the within-district variability (sd = 1.59). There was a significant Time-OPR interaction (p-value < 0.0001) indicating that as time increases the log rate of ill treatment of children has increased in the post OPR times compared to pre OPR by, on average 0.045. We expect this finding to be a direct result of the implementation of the Crime and Misconduct report into child safety issues (CMC, 2004) that resulted in 110 recommendations that were readily adopted by the State Government with $62,350,216 to be expended from 2004 to 2007 in implementing the recommendations. Random effects from this model are shown in Figure 11 below.

Figure 11: Random Effects for Reported Ill Treatment of Children Offences

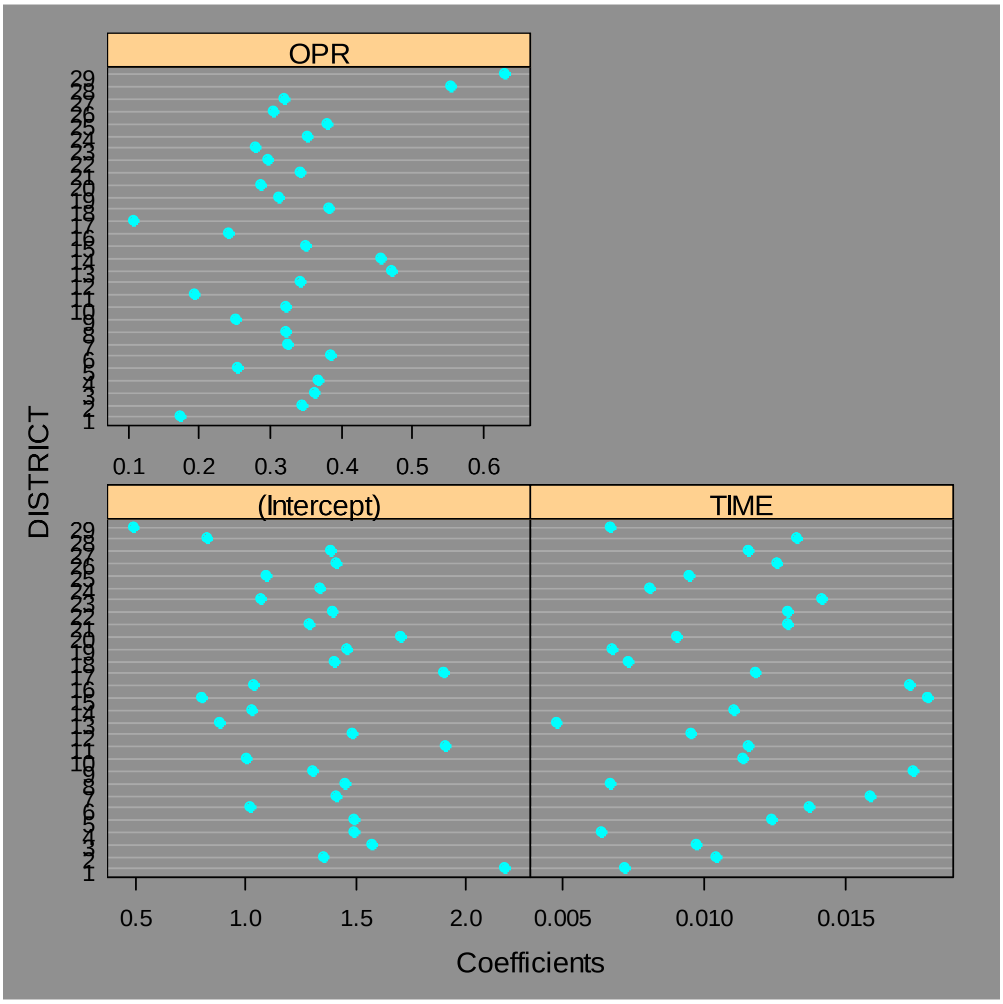


Menacing Person Offences

The natural logarithmic transformation was used for these data and an LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.40) and OPR (sd = 0.15) when compared to the within-district variability (sd = 0.64). The error term AR(1) parameter estimate is 0.111. A significant Time:OPR interaction (p-value = 0.016) indicated that, compared to pre-OPR times, the log rate of offences against the person per month is decreasing by, on average, 0.007, in post-OPR times. This category of crime reveals one of the strongest OPR effects of all the models that we examined, even considering the significant between district variability. This suggests that there are some districts (notably Districts B and F) that have positively responded to the introduction of OPRs and driven the declines across the state in offences against the person. Interestingly, District B is a city location and District F is in outback Queensland, suggesting that “type of location” is not the main factor causing the post OPR reductions in crime. Nor can the decline be attributable solely to strong leadership (as this variable in not significant in the model). We suspect that in cases of clear impact of OPR on reducing crime, yet leadership not showing up as a major contributing factor, it is likely to be characteristic of lower levels of police management that are driving the declines in crime. We are particularly interested in exploring this assertion through more detailed examination of the within-district variations in crime, most appropriately at the divisional level of analysis (see footnote 9).

There was also a significant effect of renting (p-value = 0.0001) and suggests that as the proportion of renters increase by 1 unit, the log rate of offences against the person increases by, on average, 10.43. Random effects for this model are shown in Figure 12 below.

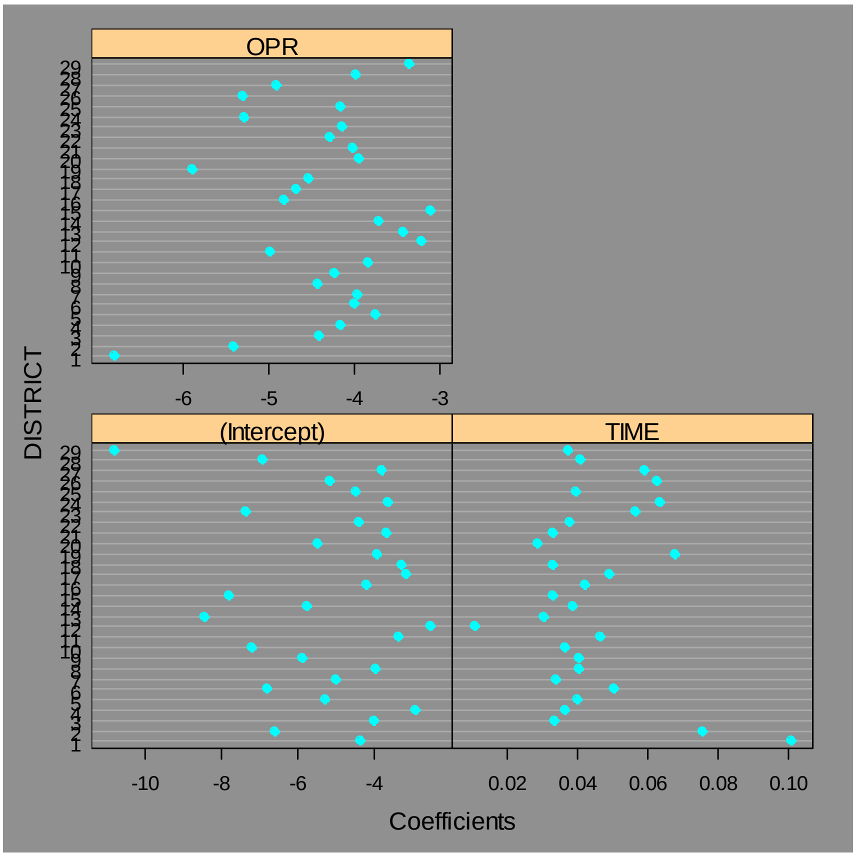
Figure 12: Random Effects for Reported Menacing Person Offences



Unlawful Entry - Dwelling

The square root transformation was used for these data and an LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the square root scale. Significant between-district variability was observed, particularly for the intercept (sd = 2.00) and OPR (sd = 0.94) when compared to the within-district variability (sd = 1.25). The error term AR(1) parameter estimate is 0.389. A positive, significant Time:OPR interaction (p-value =0.0001) indicates that, compared to pre-OPR, the monthly post-OPR square root rate of B/E from dwellings is increased by, on average, 0.053. There was also a positive and significant socio-economic disadvantage effect (p = 0.047) indicating that as disadvantage increases by 1 unit the square root of the rate of B/E from dwellings increases by, on average, 0.012. Similarly, a significant and positive proportion of overseas-born dwellers (p-value = 0.032) suggest that as the proportion of overseas dwellers increases by 1 unit, the square root of the rate of B/E from dwellings increases by, on average, 11.09. There is some indication of a seasonal effect for this variable. Note also a significant and negative Time squared effect (p <0.0001) indicating that, on average, the rate of unlawful entry into dwellings is decreasing over time, a finding consistent with the Australian and state breakdowns in average crime rates depicted in Appendix C. The random effects for this model are shown in Figure 13 below.

Figure 13: Random Effects for Reported Unlawful Entry - Dwellings

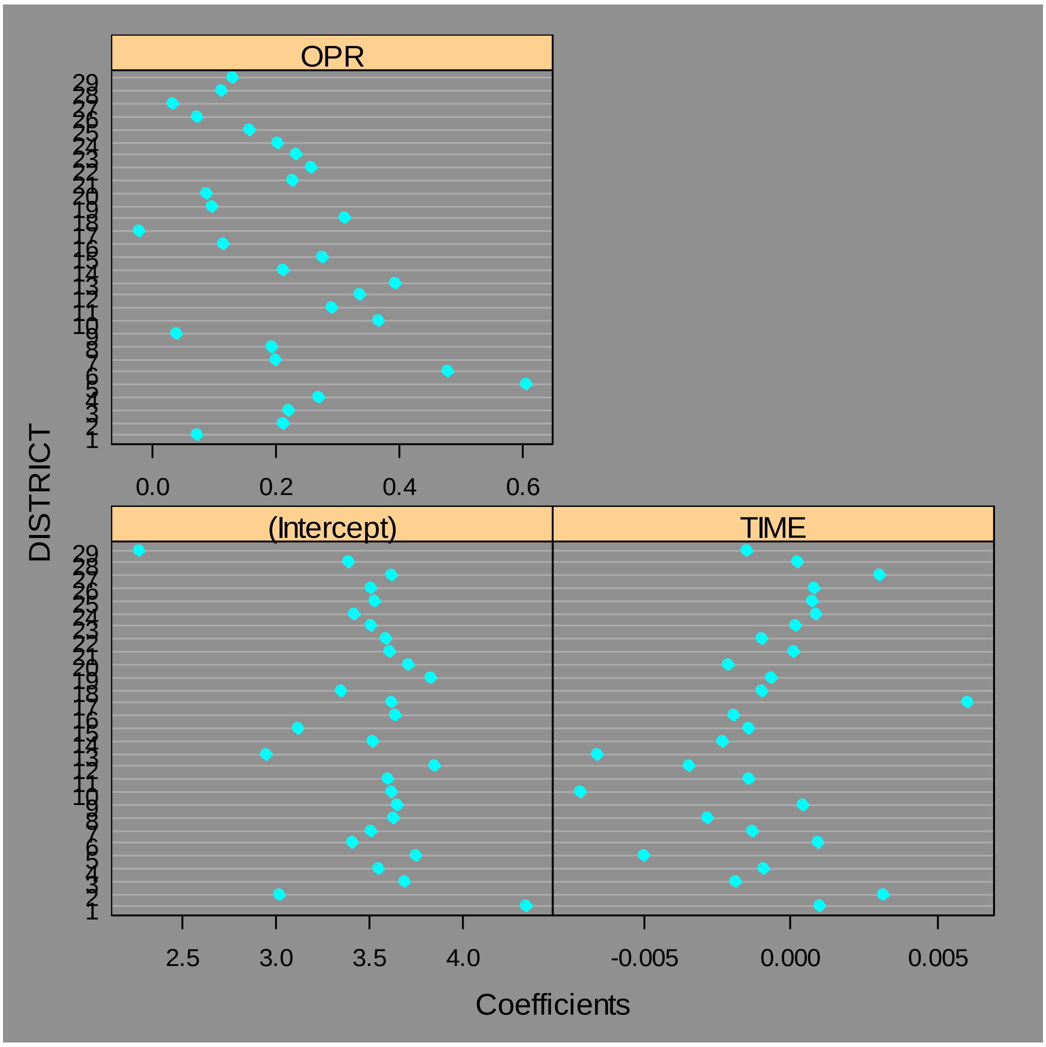


Unlawful Entry - Other Premises

The natural logarithmic transformation was used for these data and a LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed, particularly for the intercept (sd = 0.375) and OPR (sd = 0.184) when compared to the within-district variability (sd = 0.367). The error term AR(1) parameter estimate is 0.250. A negative, significant Time-OPR interaction (p = 0.034) indicates that, compared to pre-OPR, the monthly post-OPR log rate of B/E from other premises is decreasing by, on average, 0.004. Most of this decline can be attributable to the efforts of Districts A and F. The overall result is consistent with our time series results (see also Chilvers and Weatherburn, 2004) showing the important contributions that post OPR reductions in break and enter on overall state crime trends.

A positive, significant effect of the proportion renting (p = 0.0657) indicates that as the proportion renting increases by 1 unit, the log rate of B/E other premises increases by, on average, 4.68. Random effects from this model are shown in Figure 14 below.

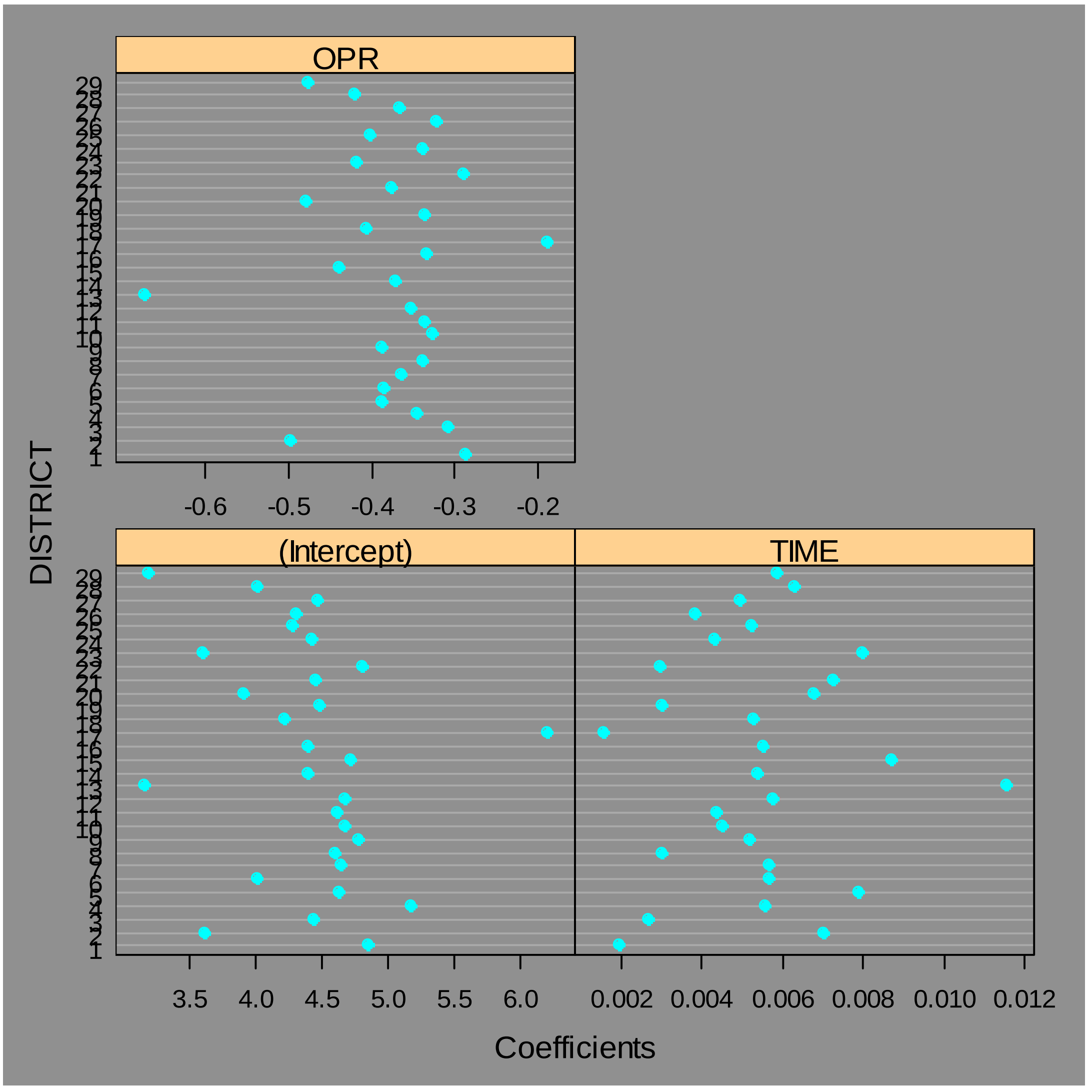
Figure 14: Random Effects for Unlawful Entry – Other Premises



Breach Domestic Violence Order

The natural logarithmic transformation was used for these data and a LMM fit. Intercept, Time, and OPR random effects terms were included. An AR(1) in the error terms was needed. All interpretations are on the log scale. Significant between-district variability was observed (Districts B and F increasing significantly the number of breaches for domestic violence orders and some of the Greater Brisbane areas contributing to the decline in DV breaches), particularly for the intercept (sd = 0.611) and OPR (sd = 0.129) when compared to the within-district variability (sd = 0.556). The error term AR(1) parameter estimate is 0.143. A positive significant Time:OPR interaction (p = 0.016) indicates that, compared to pre-OPR, the monthly post-OPR log rate of DV order breaches is increased by, on average, 0.005. A significant negative disadvantage effect (p = 0.0611) indicates that as disadvantage is increased by 1 unit, the log rate of DV breaches decreases by, on average, 0.002. There is some indication of seasonal effects for this data. Random effects from this model are shown in Figure 15 below.

Figure 15: Random Effects for Reported Breach DV Orders



Summary of the Mixed Model Analysis

Overall, the mixed model analysis described in the section above provides strong evidence for our hypothesis that there would be important variations in crime across the police districts in Queensland, that the variations would not be explained only by socio-political-economic variations and that some of the statewide crime trends post OPR would be driven in large part by the success of some districts, yet compromised by the failure of other districts. Interestingly, our district leadership measure failed to emerge as the principal reason as to why OPRs have been successful in reducing crime in Queensland, yet it was important for explaining some very specific categories of crime reduction (e.g. unlawful use of motor vehicle).

The OPR/Time variable was significant for explaining reductions in homicide, menacing person offences, break, enter and steal (other premises), and unlawful use of a motor vehicle. These results are consistent with our Stage One time series analysis. Our variable of leadership effectiveness and the willingness to adopt innovation was significant in explaining reductions in unlawful use of a motor vehicle. Social disadvantage was significant in explaining increases in total reported crime as well as break, enter and steal from dwelling. The importance of social disadvantage in influencing crime rates (see Cancino, 2005; Eck & Maguire, 2000) is well known in the criminological literature. It is interesting, however, to note that our analysis of the impact of OPRs on crime shows that two offence categories that have revealed the greatest reductions in crime following the introduction of the OPRs in Queensland were the total offence category and break and enters. This finding suggests that the OPRs can more than compensate for problems of social disadvantage.

The seasonal effect, whilst important for understanding the entire series of crime data, was particularly relevant to understanding post OPR variations in serious assault. We suspect that these seasonal patterns for interpersonal violence are largely the result of temperature and increased alcohol consumption over summer (see Bushman, Wang, & Anderson, 2005; Quigley, Leonard, & Collins, 2003).

Our mixed model results also found that the proportion of renters was significant in explaining increases in homicide, serious assaults, sexual assaults, armed robbery, unarmed robbery, menacing person offences and break and enter (other premises). These results clearly show the enduring problems in districts with high concentrations of renters, independent of social disadvantage. The criminological literature is replete with using proportion of renters as an important predictor of community crime problems (see for example Bursik, 1986; Sampson, Raudenbush, & Earls, 1997; Shaw and McKay, 1942; Skogan, 1990; Weatherburn, Lind, & Ku, 1999) and our study is entirely consistent with this tradition of ecological explanations in variations in crime.

CONCLUSIONS

This report describes the results of our impact evaluation of Queensland Police Service’s version of COMPSTAT known as “Operational Performance Reviews” (OPRs). Our study examined the impact of OPRs on reported crime in Queensland and assessed whether or not the OPRs have led to any crime reductions across the 29 police districts in Queensland. We began this report with a synopsis of the background literature that informed our research. We then presented our Stage One analysis to assess the statewide impact of introducing OPRs in Queensland in 2001. We used interrupted time series analysis to assess and isolate the direct impact that

OPRs had on different categories of crime across the state. In our second stage analysis we examined the district-by- district impact of OPRs on different categories of crime. We used a random-effects, mixed model to understand the district variations in crime as a result of introducing the OPRs.

Our project is important for several reasons: First, the fast diffusion of COMPSTAT-like programs across Australia begs the question of whether or not (or to what degree) the management strategy works to reduce crime. Second, our study sought to tease out the impact of OPRs by police district and by crime type. This part of our research contributes significantly to our understanding of how COMPSTAT-like strategies reduce some categories of crime more than others and under what types of situations. Third, our project informs police departments across Australia as to the impact of OPRs on reported crime. This information has not been previously available to Police Executives and policy makers in Australia.

There are three major findings emerging from our research: first, the impact of OPRs is different for different categories of crime. Second, the impact of OPRs varies considerably by district. Third, we suspect that there is further variation in the impact of OPRs at the smaller units of analysis (i.e., police divisions) that are potentially influencing statewide trends in data. It is the spatial variation finding (both between districts and potentially within districts) that we find most interesting. The spatial and temporal patterns in our data also hold most potential for the future of COMPSTAT-like innovations. Our findings are akin to recent longitudinal hotspot analysis using trajectory analytic techniques to model different crime patterns over time for highly specific places (hotspots). Weisburd and his colleagues (2004) for example found that some small area places (i.e., hotspots) that were strategically targeted by the police were able to alter crime trend trajectories and have a significant impact on the overall city crime rate. These results have important policy implications: first, on the one hand, it is clear that just a handful of the worst hotspots can contribute to major crime problems in a city (or district or region). On the other hand, if the police can be *effective* in reducing crime in these hotspots, then city-wide crime rates will consequently show major reductions, driven by the success in these chronic hotspots. The success in reducing crime is thus not necessarily because the police have done a great job in dealing universally with crime problems. Rather, the police can show overall success by being effective at reducing crime at just a few places.

In our evaluation of OPRs in Queensland, we find a similar pattern emerging at a much larger unit of analysis (the police district). In our study, we found that some Districts (notably Districts A and B) drove a large proportion of the decline in crime across the state. This leaves a large number of districts that could (and should) be called upon during the maturing of OPRs in Queensland to make inroads to reducing specific crime problems in their districts. If say, 10 of the remaining 27 districts could even marginally reduce their crime rates, then we would expect crime to continue to fall in Queensland over the next few years.

The second policy implication of our research centres on the question of to what extent can high specific, problem-oriented policing efforts impact not only on a district's "success" in reducing crime, but also on reducing statewide rates of specific categories of crime. The results from District G around unlawful use of a motor vehicle are instructive. Our mixed model results show that OPRs had a direct impact on reducing unlawful use of motor vehicles. Our findings also reveal that District G contributed a considerable amount to the reduction in unlawful use across the state. Personal correspondence with QPS officers reveal a concentrated effort on behalf of District G to develop crime mapping technologies, crime analysis techniques and a problem-oriented policing intervention at a large shopping centre that had problems with unlawful use of motor vehicles. This seems to suggest that highly specific problem-solving efforts have the potential to influence the state crime rate. If this is the case, then we suggest that there is an urgent need to institutionalise problem and partnership policing across all districts in Queensland. Clearly, the OPRs were set up to facilitate the adoption of problem-oriented policing in the QPS. But our results suggest that the uptake of the strategy is probably piecemeal across some divisions in some districts. This seems to suggest that there is plenty of scope for crime reductions with ongoing efforts that specifically seek to induce district commanders to adopt a problem-oriented approach to dealing with their specific district (and divisional) problems. We expect that the results of our research will help police department executives to re-think, tailor and adapt their COMPSTAT-like programs in the future.

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APPENDIX A

QPS DISTRICT CHARACTERISTICS

Region/District	Area (sq km)	Population	Police Officers	Staff Members
Far Northern Region				
Cairns	150341	161147	399	101
Innisfail	5282	34359	65	21
Mareeba	133757	43100	95	18
Northern Region				
Mount Isa	379389	31444	163	40
Townsville	169553	220162	463	129
Central Region				
Gladstone	30697	65842	131	30
Longreach	226863	11741	49	15
Mackay	69139	133248	244	48
Rockhampton	75094	129148	288	64
North Coast Region				
Bundaberg	17914	87600	132	27
Gympie	14657	70503	140	36
Maryborough	16045	92956	155	33
Redcliffe	4177	189546	294	51
Sunshine Coast	3132	284495	412	73
Southern Region				
Charleville	243019	9363	53	14
Dalby	31438	31643	57	14
Ipswich	5965	170656	321	61
Roma	114734	23404	65	19
Toowoomba	8570	169139	271	47
Warwick	27777	45340	84	21
South Eastern Region				
Logan	3405	287693	484	78
Gold Coast	1089	430515	699	95
Metro North Region				
Brisbane Central	19	53618	366	28
Brisbane West	405	200227	203	26
North Brisbane	191	206483	296	38
Pine Rivers	650	128273	122	14
Metro South Region				
Oxley	202	200025	282	41
South Brisbane	159	260741	411	52
Wynnum	646	195419	202	26

Source: Queensland Police Service Annual Statistical Review 2004/2005

APPENDIX B

CRIME CATEGORIES USED IN OPR ANALYSIS

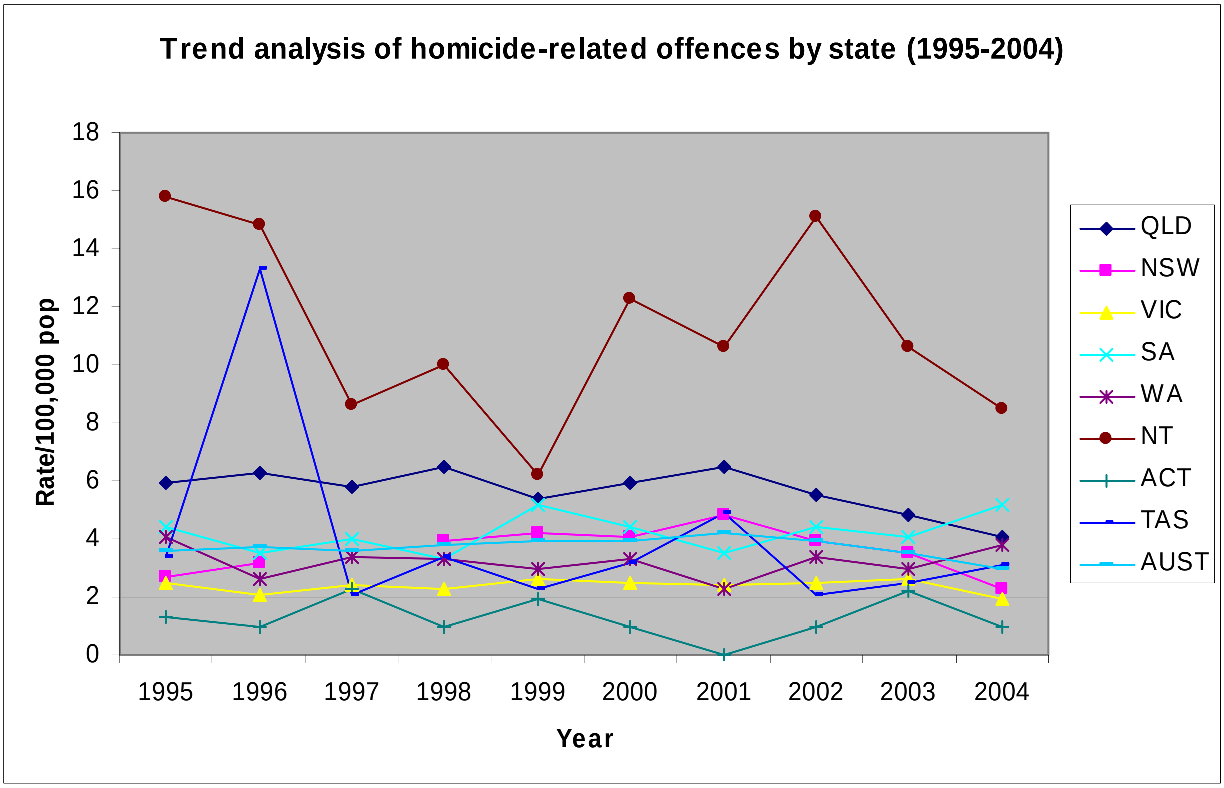
Crime Category	Crisp Codes	Crisp Code Definitions
Homicide-related Crimes	1111, 1121, 1131, 1141	Murder; Attempted murder; Conspiracy to murder; Manslaughter
Dangerous Driving	1151, 1212	Driving causing death; Driving causing GBH
Motor Vehicle Offences	3511, 3512	MV – steal, unlawful use, possess; MV – attempted steal
Serious Assaults	1211, 1221, 1222, 1223	Assault occasioning GBH; Wounding; Assault occasioning harm; Assault –serious (other)
Common Assaults	1291, 1292, 1293, 1294, 8901	Assault aggravated (non-sexual); Assault – common; Assault – police; Assault – minor (other); Assault
Sexual Offences	1361, 1362, 1363, 1365, 1366, 1364, 1371, 1372, 1373, 1391, 1392, 1393, 1394	Rape; Attempted Rape; Indecent assault on adults; Assault with intent to rape; Sexual assaults (other); Indecent treatment of children; Unlawful carnal knowledge; Incest; Sexual offence – consent proscribed; Bestiality; Gross indecency; Wilful indecent exposure; Sexual offence (other)
Armed Robbery	2111	Robbery – armed
Unarmed Robbery	2121, 2122, 2123, 2124	Robbery – unarmed; Robbery – unarmed in company; Assault with intent to steal; Demand property
Ill Treatment of Children	1921	Ill treatment of children
Menacing Person Offences	1991, 1992, 1993, 5991	Armed so as to cause fear; Offences against the person; Stalking; Armed with intent
Unlawful Entry - Dwelling	3111, 3112, 3113, 3114, 3991, 8905,	Burglary with breaking; Burglary; Burglary – with violence or threats – with breaking; Burglary – with violence or threats; Stealing from dwelling houses; Unlawful entry of a house
Unlawful Entry – Other Premises	3191, 3121, 3122, 3181, 3182, 3931, 3992	B/E – buildings; B/E with intent – shop; Enter shop with intent; B/E with intent – buildings; Enter with intent – buildings; Shop steal UTAG; Steal from other building
Breach Domestic Violence Orders	5495	DV Breach (Family Protection Act)

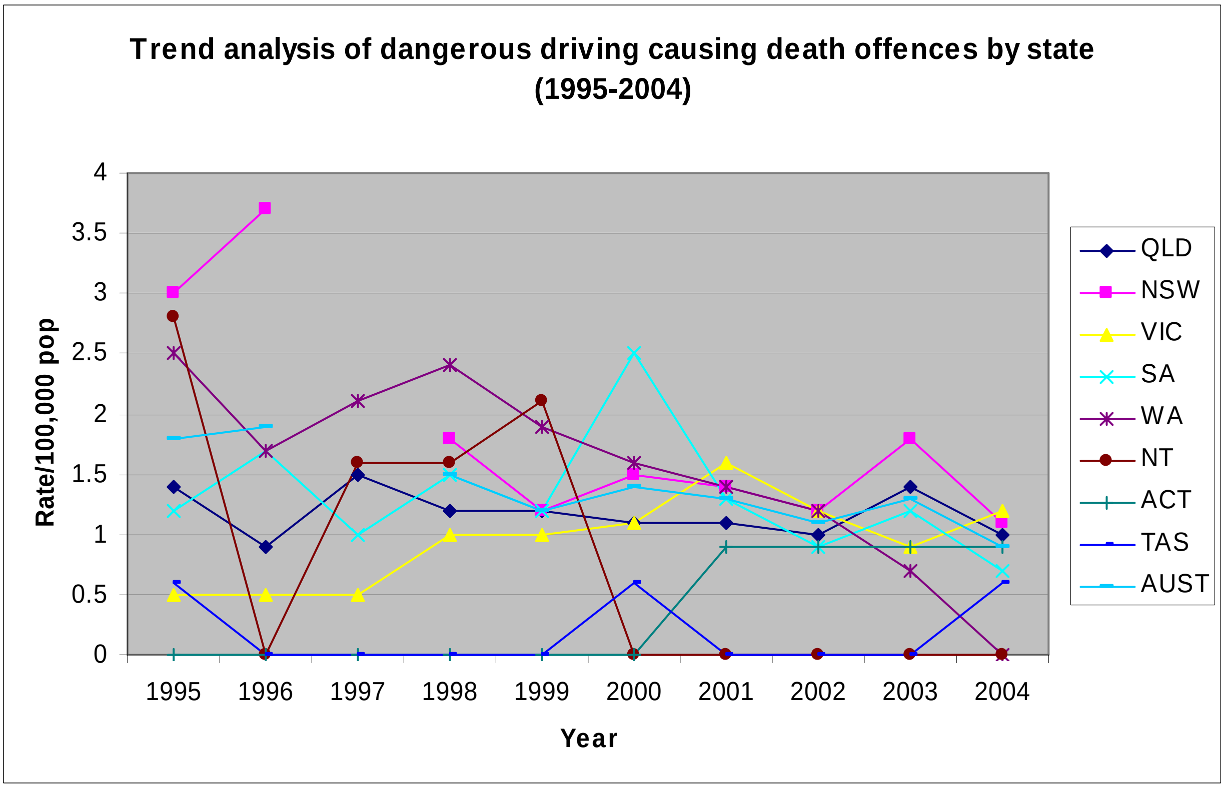
APPENDIX C

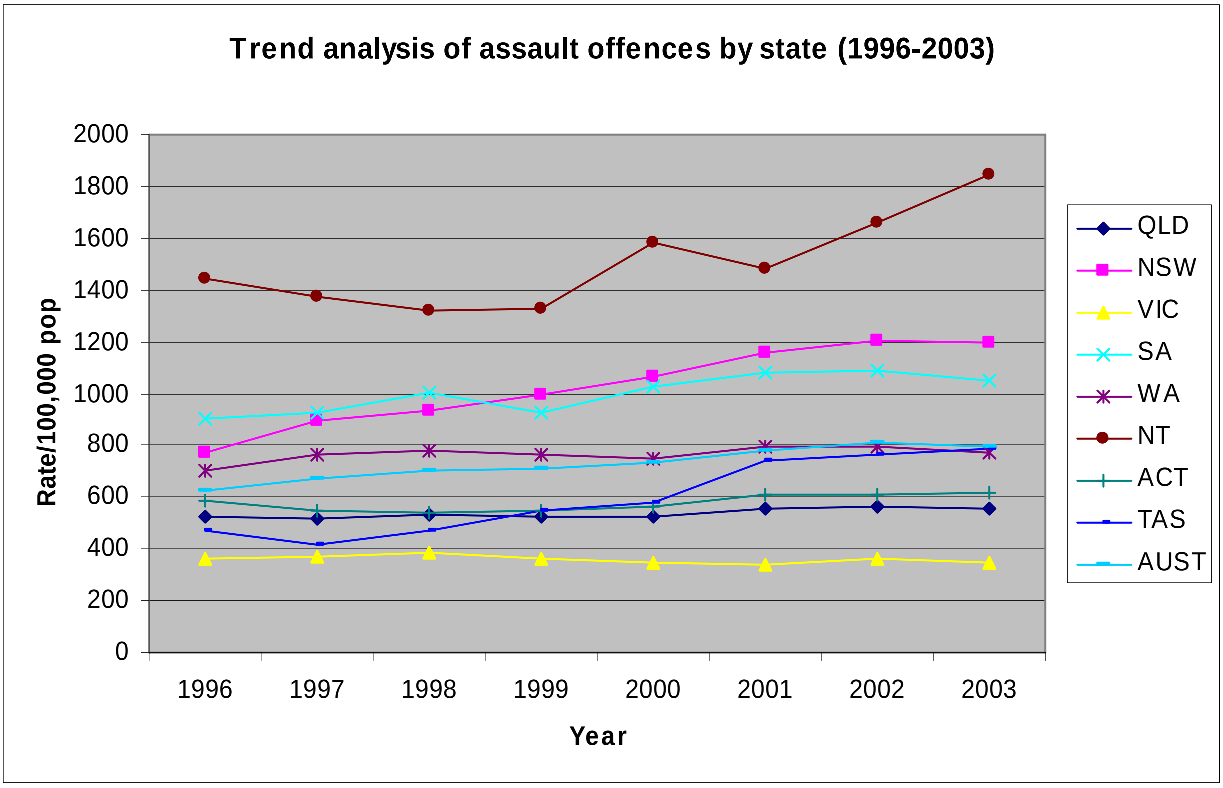
CRIME TRENDS IN AUSTRALIAN STATES (1995 – 2004)

Data from graphs sourced from Australian Bureau of Statistics.

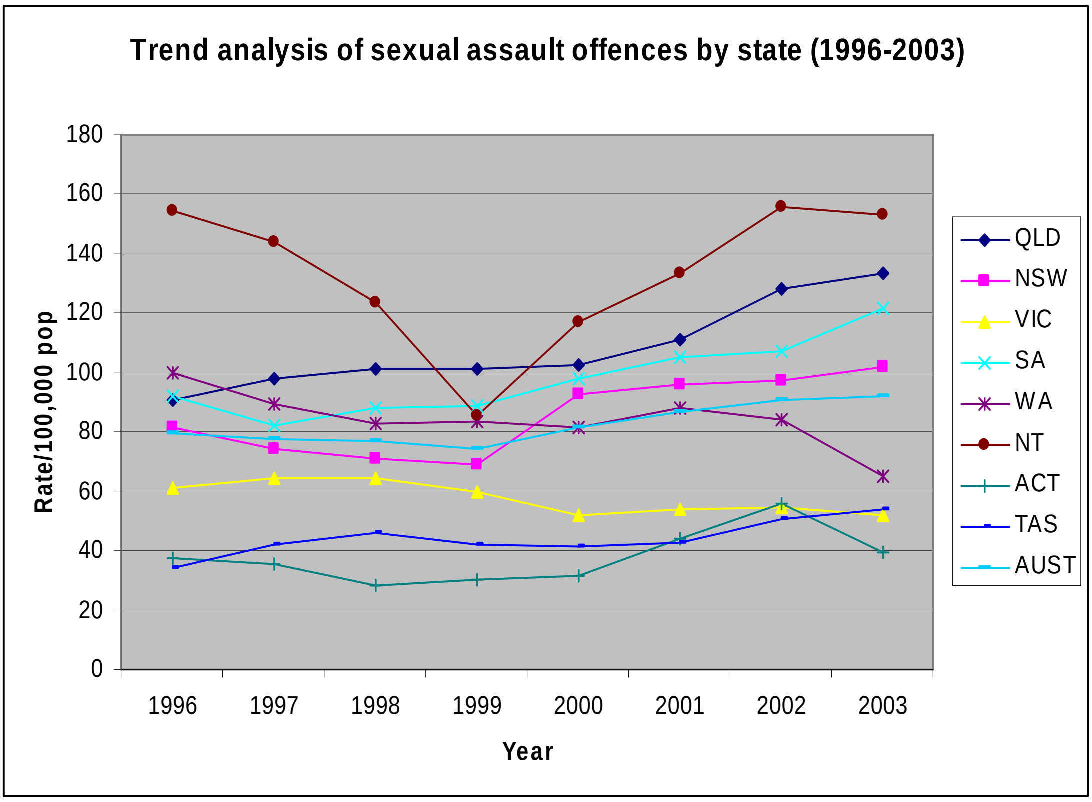
“Recorded Crime - Victims, Australia” series 1997-2004 (4510.0)


Trend analysis of homicide-related offences by state (1995-2004)
Rate/100,000 pop
18
16
14
12
10
8
6
4
2
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST

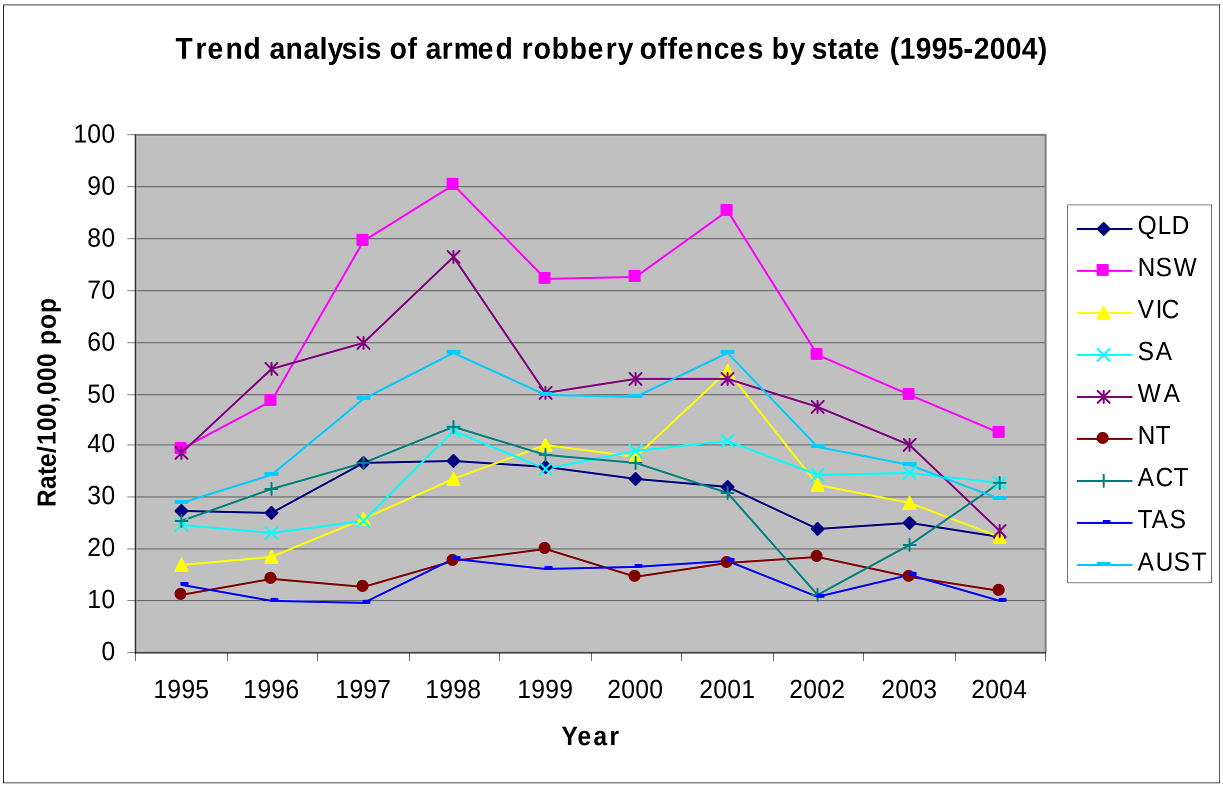

Trend analysis of dangerous driving causing death offences by state (1995-2004)
Rate/100,000 pop
4
3.5
3
2.5
2
1.5
1
0.5
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST

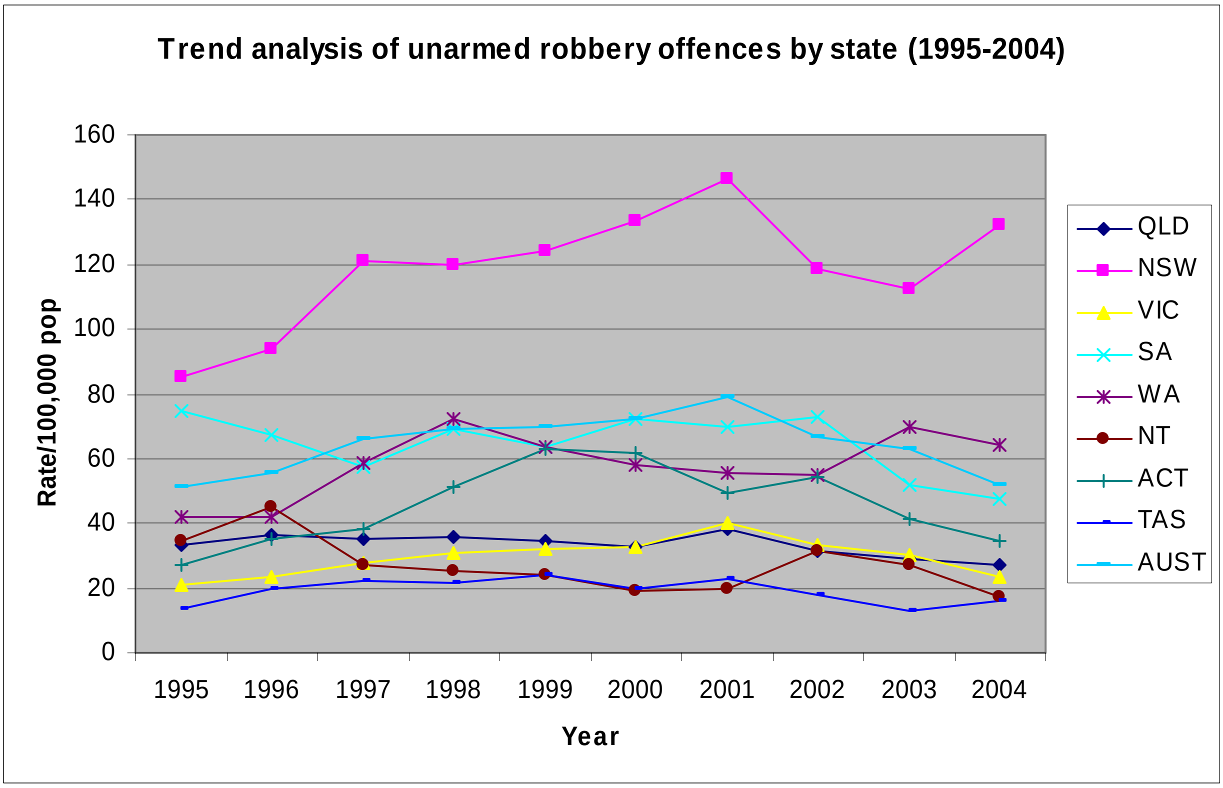


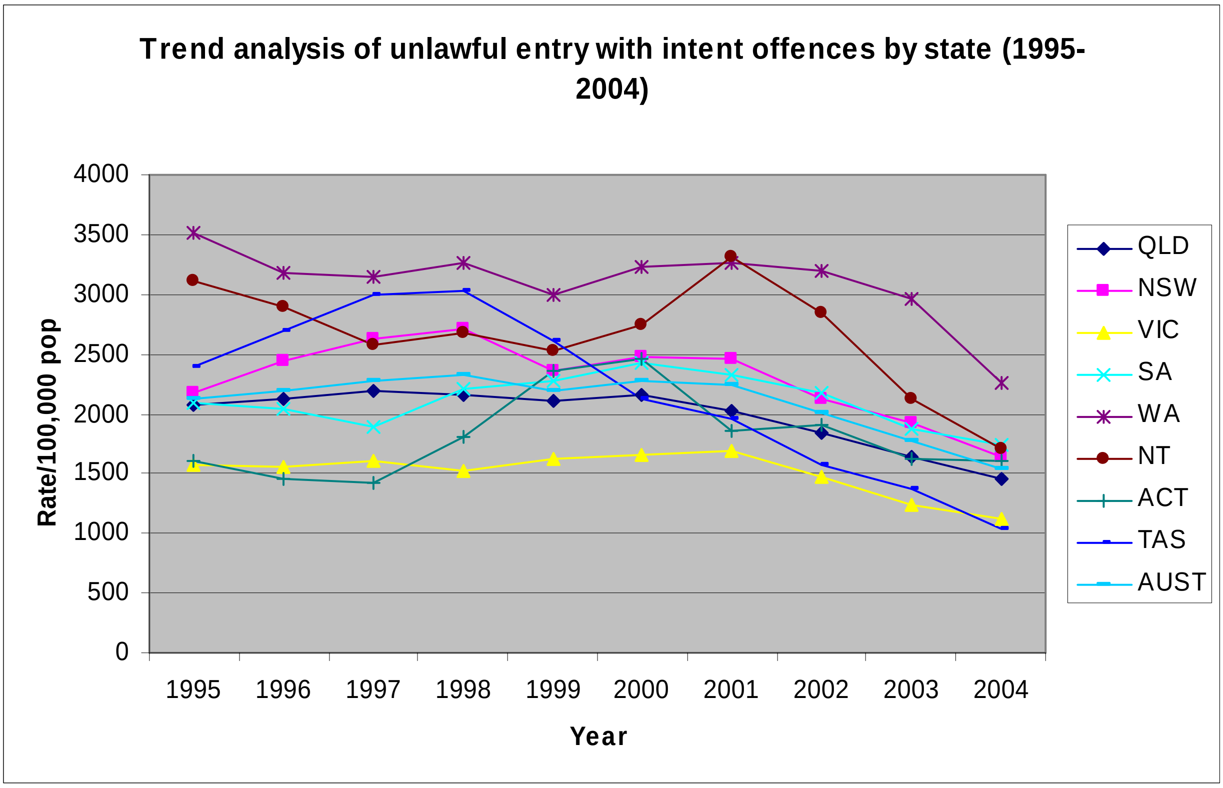
Trend analysis of assault offences by state (1996-2003)
Rate/100,000 pop
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST



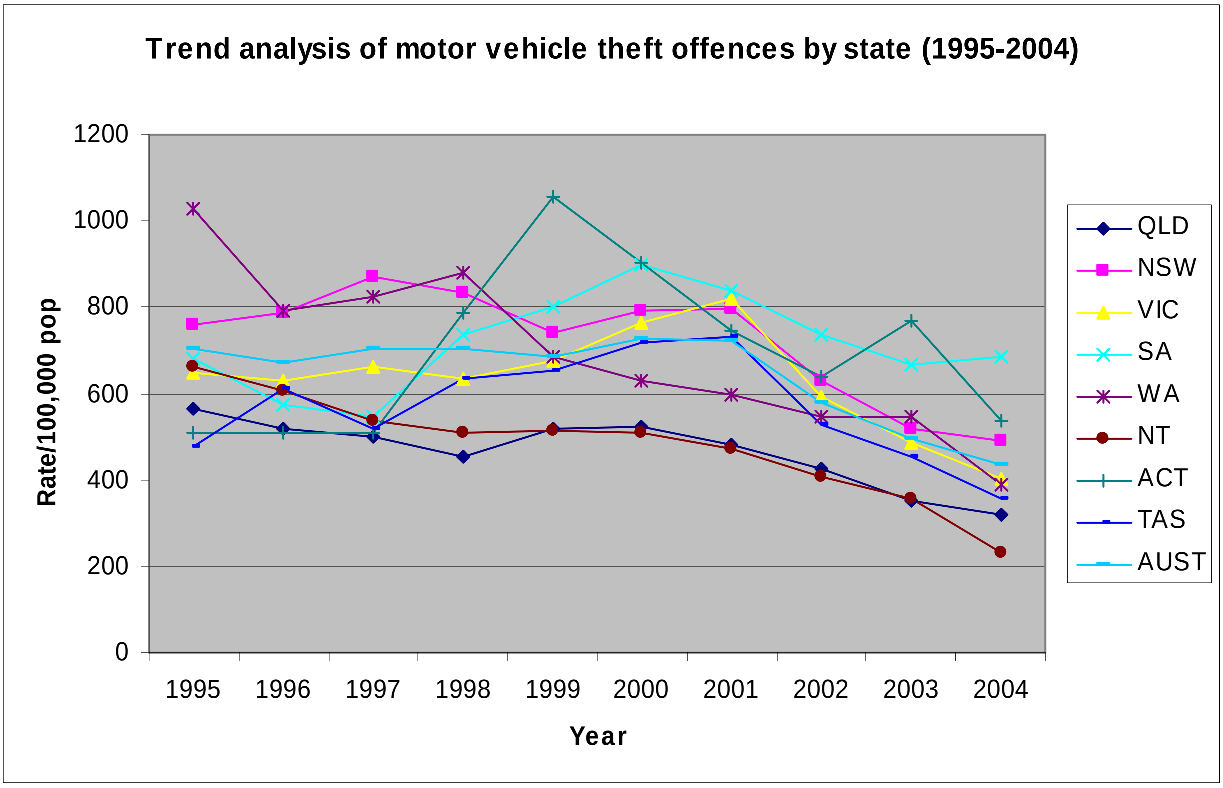
Trend analysis of sexual assault offences by state (1996-2003)
Rate/100,000 pop
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST


Trend analysis of armed robbery offences by state (1995-2004)
Rate/100,000 pop
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST


Trend analysis of unarmed robbery offences by state (1995-2004)
Rate/100,000 pop
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST



Trend analysis of unlawful entry with intent offences by state (1995-2004)
Rate/100,000 pop
4000
3500
3000
2500
2000
1500
1000
500
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST



Trend analysis of motor vehicle theft offences by state (1995-2004)
Rate/100,000 pop
1200
1000
800
600
400
200
0
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
Year
QLD
NSW
VIC
SA
WA
NT
ACT
TAS
AUST

APPENDIX D

SUMMARY STATISTICS FROM MIXED MODEL ANALYSIS

Homicide – Related:

```
Random effects:
 Formula: ~1 | DISTRICT
        (Intercept) Residual
StdDev:   0.3254539 1.221045

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: X1 ~ TIME * OPR + Leader + MP1 + pop + season +
I(oversea/pop) +      I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     1.639701 1.5098001 3091  1.086039  0.2775
TIME           -0.000579 0.0017093 3091 -0.338709  0.7349
OPR             0.845297 0.4979241 3091  1.697641  0.0897
Leader          0.143747 0.1115303 3091  1.288858  0.1975
MP1            -0.021157 0.0122749 3091 -1.723598  0.0849
pop             0.000005 0.0000010 3091  4.438951  0.0000
seasonSpring    0.127732 0.0832336 3091  1.534622  0.1250
seasonSummer    0.034903 0.0842234 3091  0.414412  0.6786
seasonWinter   -0.044679 0.0859413 3091 -0.519880  0.6032
I(oversea/pop)  1.564683 1.5424405 3091  1.014420  0.3105
I(rent/pop)    11.192083 2.9975489 3091  3.733745  0.0002
dis            -0.004331 0.0015625 3091 -2.771688  0.0056
TIME:OPR       -0.010326 0.0057255 3091 -1.803425  0.0714

Intercept:
[1] 29 13 23  8 28 25  2 15  7 10  5 14  6 16 18  1 19 21 26 17 24  9
4 12 11
[26] 20 27 22  3
```

Dangerous Driving:

```
Random effects:
 Formula: ~TIME | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.202759440 (Intr)
TIME        0.005688955 -0.983
Residual    1.236082536

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: X2 ~ TIME * OPR + Leader + MP2 + pop + season +
I(oversea/pop) +      I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     3.462550 1.4379263 3091  2.408016  0.0161
TIME            0.000623 0.0029031 3091  0.214507  0.8302
OPR             0.835006 0.6961133 3091  1.199526  0.2304
Leader          0.254102 0.1003546 3091  2.532039  0.0114
MP2            -0.043571 0.0291302 3091 -1.495748  0.1348
pop             0.000008 0.0000008 3091 10.082458  0.0000
seasonSpring    0.031075 0.1239482 3091  0.250706  0.8021
seasonSummer   -0.050704 0.1253483 3091 -0.404502  0.6859
seasonWinter   -0.026888 0.1247686 3091 -0.215505  0.8294
I(oversea/pop) -1.774015 1.1946092 3091 -1.485017  0.1376
I(rent/pop)     3.448354 2.7802607 3091  1.240299  0.2150
dis            -0.006246 0.0014800 3091 -4.220558  0.0000
TIME:OPR       -0.008907 0.0080407 3091 -1.107737  0.2681
```

```
Intercept:
[1] 14 26 24 20 28 12 27 21  3  5  7 23 29 16  6  9  2  1 10 19  4 15
18 13 25
[26] 17 22 11  8

Time:
[1]  8 11 18 22 13 15 17 25  4 19  2  6 16 10  9  1 29 23  7  5  3 21
27 12 20
[26] 28 24 26 14
```

Serious Assault:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  2857.945 2972.811 -1409.972

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.604284329 (Intr) TIME
TIME        0.002670239 -0.427
OPR         0.072647563 -0.326 -0.656
Residual    0.363488057

Fixed effects: log((X2a/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP2A + season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     3.194851 0.8680979 3092  3.680288  0.0002
TIME            0.000107 0.0006505 3092  0.164283  0.8695
OPR             0.197799 0.1250650 3092  1.581567  0.1139
Leader          0.033280 0.0399024 3092  0.834039  0.4043
MP2A            0.000080 0.0001182 3092  0.675256  0.4996
seasonSpring    0.062626 0.0186411 3092  3.359585  0.0008
seasonSummer    0.117877 0.0184287 3092  6.396389  0.0000
seasonWinter   -0.092277 0.0184368 3092 -5.005057  0.0000
I(oversea/pop) -2.393911 1.3186510 3092 -1.815424  0.0696
I(rent/pop)     3.704450 2.1892586 3092  1.692103  0.0907
dis            -0.000086 0.0008612 3092 -0.099320  0.9209
TIME:OPR       -0.002160 0.0014287 3092 -1.511711  0.1307

OPR:
[1] 17 16  1  7  3 22  4 23 12 21 10 11 26 25  9  8 28 15 27  2 14  6
24 20 19
[26]  5 18 29 13
```

Common Assault:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  4042.895 4157.761 -2002.447

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.556288278 (Intr) TIME
TIME        0.002409303 -0.102
OPR         0.132235196 -0.132 -0.499
```

```
Residual    0.439749076

Fixed effects: log((X2b/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP2B + season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     1.710492 1.0115192 3092  1.691013  0.0909
TIME            0.001198 0.0006974 3092  1.717817  0.0859
OPR            -0.128046 0.1504346 3092 -0.851177  0.3947
Leader         -0.037570 0.0506091 3092 -0.742352  0.4579
MP2B           -0.000161 0.0002121 3092 -0.760344  0.4471
seasonSpring    0.118778 0.0225578 3092  5.265503  0.0000
seasonSummer    0.146074 0.0222942 3092  6.552103  0.0000
seasonWinter   -0.004468 0.0223046 3092 -0.200297  0.8413
I(oversea/pop) -2.072451 1.6039896 3092 -1.292060  0.1964
I(rent/pop)     3.721028 2.8882127 3092  1.288350  0.1977
dis             0.001010 0.0010298 3092  0.981230  0.3266
TIME:OPR        0.000941 0.0017065 3092  0.551517  0.5813

OPR:
[1] 10  6  1 26 25  4  8 14  5 24 28 16 29 12 17  3 11  7 21 19 27 20
9 15  2
[26] 23 13 18 22
```

Sexual Offences (Combined):

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  7752.006 7872.918 -3856.003

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.443692007 (Intr) TIME
TIME        0.002301721 -0.085
OPR         0.199501060  0.040 -0.733
Residual    0.806672850

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
       Phi
0.03789018
Fixed effects: log((sexual/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
Morans +      season + I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     2.046424  1.263294 3092  1.619910  0.1054
TIME            0.003467  0.000993 3092  3.490543  0.0005
OPR            -0.093636  0.260472 3092 -0.359487  0.7193
Leader         -0.106161  0.081237 3092 -1.306811  0.1914
Morans          0.000874  0.000693 3092  1.262069  0.2070
seasonSpring    0.190380  0.042317 3092  4.498905  0.0000
seasonSummer    0.053595  0.041630 3092  1.287402  0.1981
seasonWinter    0.013989  0.041619 3092  0.336117  0.7368
I(oversea/pop)  0.260042  1.413193 3092  0.184010  0.8540
I(rent/pop)     6.364520  3.265672 3092  1.948916  0.0514
dis            -0.000594  0.001308 3092 -0.453820  0.6500
TIME:OPR       -0.000299  0.002927 3092 -0.102322  0.9185

OPR:
```

```
[1] 17 26 20  1  8  2 19 16 13 25  5 12 18 24 11  9 15 23  3 21  6 27
29  7  4
[26] 28 22 10 14
```

Armed Robbery:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  4632.857 4729.586 -2300.428

Random effects:
 Formula: ~TIME | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.374878696 (Intr)
TIME        0.000861527 -0.768
Residual    0.489902232

Fixed effects: log((X4b/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP4B + season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)    -0.471244 0.8131965 3092 -0.579496  0.5623
TIME            0.002434 0.0005824 3092  4.180293  0.0000
OPR            -0.076721 0.1510585 3092 -0.507890  0.6116
Leader         -0.049350 0.0477761 3092 -1.032935  0.3017
MP4B            0.005165 0.0013310 3092  3.880466  0.0001
seasonSpring    0.049117 0.0250778 3092  1.958577  0.0503
seasonSummer   -0.013484 0.0248320 3092 -0.543003  0.5872
seasonWinter    0.029489 0.0248444 3092  1.186952  0.2353
I(oversea/pop)  5.017347 0.9916200 3092  5.059747  0.0000
I(rent/pop)     4.453270 2.0094751 3092  2.216136  0.0268
dis            -0.000025 0.0008284 3092 -0.029671  0.9763
TIME:OPR       -0.002097 0.0017665 3092 -1.186895  0.2354

Intercept:
[1] 29 10 15  2 13  7  5  8  9 23 19 16 28 25 14 17 18 20  6  3 12  4
27 21 22
[26] 24 26 11  1

Time:
[1]  1 11 26 24  4 21 12 27  3  6 18 22 20 25  8 17 16 14 23 19  7 13
5 28  9
[26]  2 10 15 29
```

Unarmed Robbery:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  4875.912 4996.824 -2417.956

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.450018983 (Intr) TIME
TIME        0.002630362 -0.529
OPR         0.174050763  0.039 -0.819
Residual    0.507418347
```

```
Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
       Phi
0.04532006
Fixed effects: log((X4c/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP4C + season +      I(oversea/pop) + I(rent/pop) + dis
                    Value Std.Error   DF   t-value p-value
(Intercept)    -0.869736 0.9471534 3092 -0.918263  0.3586
TIME           -0.000498 0.0007528 3092 -0.662190  0.5079
OPR             0.028431 0.1671948 3092  0.170047  0.8650
Leader          0.038131 0.0541913 3092  0.703641  0.4817
MP4C           -0.001048 0.0012874 3092 -0.814206  0.4156
seasonSpring    0.004150 0.0267275 3092  0.155279  0.8766
seasonSummer   -0.008786 0.0262701 3092 -0.334443  0.7381
seasonWinter   -0.014720 0.0262585 3092 -0.560592  0.5751
I(oversea/pop)  4.505414 1.0042081 3092  4.486534  0.0000
I(rent/pop)     8.395038 2.0799986 3092  4.036078  0.0001
dis             0.000364 0.0009685 3092  0.375468  0.7073
TIME:OPR       -0.001785 0.0018903 3092 -0.944420  0.3450

OPR:
[1]  5 26  1 16 25 22  3 23 24  7  9 12  8 19 15 27 17  2  6 13 20 29
11 28 21
[26] 10 14  4 18
```

Ill Treatment of Children:

```
Random effects:
 Formula: ~TIME | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev     Corr
(Intercept) 1.10977140 (Intr)
TIME        0.02056733 -0.698
Residual    1.58511556

Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: X7a ~ TIME * OPR + Leader + MP7A + pop + season +
I(oversea/pop) +      I(rent/pop) + dis
                    Value Std.Error   DF   t-value p-value
(Intercept)    -4.415208  2.899689 3091 -1.522649  0.1279
TIME            0.009393  0.004598 3091  2.042883  0.0411
OPR            -3.539727  0.403465 3091 -8.773329  0.0000
Leader          0.116281  0.165257 3091  0.703641  0.4817
MP7A           -0.002655  0.001588 3091 -1.672016  0.0946
pop             0.000010  0.000002 3091  4.162729  0.0000
seasonSpring   -0.045552  0.067392 3091 -0.675921  0.4991
seasonSummer    0.018286  0.061660 3091  0.296569  0.7668
seasonWinter   -0.154795  0.065519 3091 -2.362589  0.0182
I(oversea/pop)  3.449001  3.435460 3091  1.003942  0.3155
I(rent/pop)    -1.548197  6.690546 3091 -0.231401  0.8170
dis             0.001474  0.003049 3091  0.483453  0.6288
TIME:OPR        0.045219  0.004726 3091  9.568797  0.0000

Intercept:
[1]  4 17 15  2 11 29  5 10 18  3 28  7 14 27 13 23  8  6 22 24  9 19
12 25  1
[26] 20 26 16 21
```

```
Time:
[1]  8 14 24 13 12 29 23 26  1 21 28  6 20 19 25  7 16  9  2 10  5 18
22  3 27
[26] 11 15  4 17
```

Other Offences Against the Person:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  6274.643 6395.554 -3117.321

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.395949864 (Intr) TIME
TIME        0.004209394 -0.273
OPR         0.153465176 -0.475 -0.376
Residual    0.637892298

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.1112659
Fixed effects: log((X7b/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP7B + season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     1.318434 1.2053936 3092  1.093779  0.2741
TIME            0.011040 0.0014309 3092  7.714902  0.0000
OPR             0.335603 0.2570939 3092  1.305370  0.1919
Leader          0.115899 0.0710542 3092  1.631134  0.1030
MP7B           -0.000366 0.0009169 3092 -0.398767  0.6901
seasonSpring    0.118816 0.0348771 3092  3.406713  0.0007
seasonSummer    0.036235 0.0338716 3092  1.069763  0.2848
seasonWinter   -0.001967 0.0338145 3092 -0.058183  0.9536
I(oversea/pop)  1.623444 1.1226006 3092  1.446145  0.1482
I(rent/pop)    10.434258 2.6981718 3092  3.867159  0.0001
dis            -0.001408 0.0012564 3092 -1.120917  0.2624
TIME:OPR       -0.007435 0.0030884 3092 -2.407248  0.0161

OPR:
[1] 17  1 11 16  9  5 23 20 22 26 19 27  8 10  7 21 12  2 15 24  3  4
25 18  6
[26] 14 13 28 29
```

Break/Enter Steal from Dwelling:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  10057.09 10184.04 -5007.546

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev     Corr
(Intercept) 2.00942935 (Intr) TIME
TIME        0.01917840 -0.034
OPR         0.93805950 -0.316 -0.853
```

```
Residual    1.24610176

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.3891155
Fixed effects: sqrt((X8a/pop) * 1e+05) ~ TIME * OPR + Leader + MP8A +
I(TIME^2) +      season + I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)    -5.165903  4.068712 3091 -1.269665  0.2043
TIME            0.044736  0.009768 3091  4.579909  0.0000
OPR            -4.372921  0.996242 3091 -4.389419  0.0000
Leader         -0.154597  0.192240 3091 -0.804187  0.4214
MP8A            0.000430  0.000217 3091  1.977596  0.0481
I(TIME^2)      -0.000616  0.000118 3091 -5.212657  0.0000
seasonSpring   -0.313448  0.073465 3091 -4.266642  0.0000
seasonSummer    0.061384  0.067553 3091  0.908676  0.3636
seasonWinter   -0.513908  0.067308 3091 -7.635190  0.0000
I(oversea/pop) 11.099608  5.169240 3091  2.147242  0.0319
I(rent/pop)     3.421126 10.225203 3091  0.334578  0.7380
dis             0.011719  0.004147 3091  2.825741  0.0047
TIME:OPR        0.052931  0.013382 3091  3.955539  0.0001

OPR:
[1]  1 19  2 26 24 11 27 16 17 18  8  3 22  9  4 25 23 21  6 28  7 20
10  5 14
[26] 13 29 12 15
```

Break/Enter all Other Premises:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  2697.446 2818.358 -1328.723

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev      Corr
(Intercept) 0.375157116 (Intr) TIME
TIME        0.003308835 -0.063
OPR         0.184373136 -0.019 -0.661
Residual    0.366691779

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.2502652
Fixed effects: log((X8b/pop) * 1e+05 + 1) ~ TIME * OPR + Leader +
MP8B + season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     3.509606 0.9125142 3092  3.846083  0.0001
TIME           -0.000856 0.0008158 3092 -1.049531  0.2940
OPR             0.212926 0.1620610 3092  1.313864  0.1890
Leader          0.005787 0.0505703 3092  0.114442  0.9089
MP8B            0.000105 0.0000625 3092  1.682440  0.0926
seasonSpring   -0.062818 0.0212305 3092 -2.958866  0.0031
seasonSummer   -0.043158 0.0200628 3092 -2.151129  0.0315
seasonWinter   -0.045573 0.0199873 3092 -2.280113  0.0227
```

```
I(oversea/pop)  0.212977 1.1779388 3092  0.180805  0.8565
I(rent/pop)     4.683224 2.5433304 3092  1.841375  0.0657
dis             0.000169 0.0009551 3092  0.177092  0.8594
TIME:OPR       -0.003962 0.0018682 3092 -2.120967  0.0340

OPR:
[1] 17 27  9 26  1 20 19 28 16 29 25  8  7 24 14  2  3 21 23 22  4 15
11 18 12
[26] 10 13  6  5
```

Unlawful Use of Motor Vehicle:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC      BIC    logLik
  9408.902 9535.852 -4683.451

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev     Corr
(Intercept) 1.63465390 (Intr) TIME
TIME        0.01314730 -0.002
OPR         0.81914194 -0.260 -0.921
Residual    1.05781559

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.2097348
Fixed effects: sqrt((X8c/pop) * 1e+05) ~ TIME * OPR + Leader + MP8C +
I(TIME^2) +      season + I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     0.665036  2.887567 3091  0.230310  0.8179
TIME           -0.011968  0.006355 3091 -1.883314  0.0598
OPR             1.862270  0.702822 3091  2.649706  0.0081
Leader         -0.355041  0.142563 3091 -2.490413  0.0128
MP8C            0.001204  0.000345 3091  3.487056  0.0005
I(TIME^2)       0.000153  0.000077 3091  2.003846  0.0452
seasonSpring   -0.065928  0.060440 3091 -1.090788  0.2755
seasonSummer   -0.071395  0.057580 3091 -1.239927  0.2151
seasonWinter   -0.127413  0.057484 3091 -2.216483  0.0267
I(oversea/pop) 11.546269  4.054323 3091  2.847890  0.0044
I(rent/pop)     4.309127  7.351581 3091  0.586150  0.5578
dis             0.002872  0.002877 3091  0.998004  0.3184
TIME:OPR       -0.031273  0.009300 3091 -3.362559  0.0008

OPR:
[1]  1 21 24  9 27 25  2 28  6 14 20 19  8  7 23 26 11 29 22 13 16 15
4  3 17
[26] 12 18 10  5
```

Breach Domestic Violence Order:

```
Linear mixed-effects model fit by REML
 Data: new.crime
      AIC      BIC    logLik
  5397.19 5518.101 -2678.595

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
```

```
             StdDev      Corr
(Intercept) 0.611169811 (Intr) TIME
TIME        0.002964152 -0.535
OPR         0.129408590  0.606 -0.806
Residual    0.555781868

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.1426603
Fixed effects: log((X9/pop) * 1e+05 + 1) ~ TIME * OPR + Leader + MP9
+ season +      I(oversea/pop) + I(rent/pop) + dis
                   Value Std.Error   DF   t-value p-value
(Intercept)     4.408827  1.125810 3092  3.916139  0.0001
TIME            0.005382  0.000965 3092  5.577669  0.0000
OPR            -0.377669  0.195624 3092 -1.930583  0.0536
Leader          0.017392  0.065074 3092  0.267264  0.7893
MP9             0.000678  0.000261 3092  2.593159  0.0096
seasonSpring   -0.011046  0.030884 3092 -0.357676  0.7206
seasonSummer    0.115277  0.029800 3092  3.868327  0.0001
seasonWinter   -0.105408  0.029733 3092 -3.545122  0.0004
I(oversea/pop) -1.239476  1.647712 3092 -0.752240  0.4520
I(rent/pop)    -0.458015  3.260189 3092 -0.140487  0.8883
dis            -0.002150  0.001147 3092 -1.873763  0.0611
TIME:OPR        0.005331  0.002204 3092  2.418712  0.0156

OPR:
[1] 13  2 20 29 15 28 23 18 25  9  5  6 21 14 27  7 12  4  8 24 19 11
16 10 26
[26]  3 22  1 17
```

Total Reported Offences:

```
Linear mixed-effects model fit by REML
 Data: new.crime
       AIC       BIC   logLik
  -1214.406 -1087.455 628.2029

Random effects:
 Formula: ~TIME + OPR | DISTRICT
 Structure: General positive-definite, Log-Cholesky parametrization
             StdDev      Corr
(Intercept) 0.510092627 (Intr) TIME
TIME        0.001954025 -0.062
OPR         0.098485259 -0.012 -0.711
Residual    0.198622887

Correlation Structure: AR(1)
 Formula: ~TIME | DISTRICT
 Parameter estimate(s):
      Phi
0.3264307
Fixed effects: log((X10/pop) * 1e+05 + 1) ~ TIME * OPR + Leader + MP
+ I(TIME^2) +      season + I(oversea/pop) + I(rent/pop) + dis
                    Value Std.Error   DF   t-value p-value
(Intercept)     2.7342719 0.7066991 3091  3.869075  0.0001
TIME            0.0071049 0.0013110 3091  5.419605  0.0000
```

```
OPR            -0.5226514 0.1572549 3091 -3.323593  0.0009
Leader         -0.0351521 0.0301352 3091 -1.166478  0.2435
MP             -0.0000112 0.0000050 3091 -2.237437  0.0253
I(TIME^2)      -0.0000906 0.0000178 3091 -5.094034  0.0000
seasonSpring   -0.0190149 0.0116882 3091 -1.626852  0.1039
seasonSummer    0.0078945 0.0108731 3091  0.726053  0.4679
seasonWinter   -0.0638250 0.0108423 3091 -5.886672  0.0000
I(oversea/pop)  0.3488812 1.4009265 3091  0.249036  0.8033
I(rent/pop)    -0.2399487 2.1580083 3091 -0.111190  0.9115
dis             0.0028194 0.0006733 3091  4.187609  0.0000
TIME:OPR        0.0065916 0.0021521 3091  3.062860  0.0022

OPR:
[1] 26  2  1 19 20 27 24  9 16 17 25 29 28 11 21  4  3  8  7 18 15 14
23  6 22
[26] 10 13 12  5
```