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Crime by outlaw motorcycle gang members during club conflicts

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Abstract | This study examines the trends in and spatial distribution of recorded offending by Australian outlaw motorcycle gang (OMCG) affiliates at the onset of a territorial conflict between two clubs in the state of New South Wales.

Results show an increase in recorded offending by OMCG affiliates involved in the conflict and based in the disputed territory. Comparable increases in recorded offending by these clubs were not detected in the areas surrounding this territory or in the rest of New South Wales, and there was little mobility into the conflict region by those outside of it. There was a smaller, short-lived increase in recorded crime by affiliates of other gangs in the conflict region but not elsewhere. In short, changes in offending patterns were largely limited to the clubs involved in the conflict and localised to the territory in dispute.

This research can help guide focused law enforcement responses during periods of gang conflict.

From their origins in the United States, outlaw motorcycle gangs (OMCGs) have spread across the globe (Lauchs 2020). Over the twentieth and early twenty-first centuries, clubs have proliferated and pushed into new areas, cementing their presence with semi-independent regional chapters (Quinn & Forsyth 2011). The Australian Criminal Intelligence Commission (2021) has identified 38 OMCGs currently operating in Australia, collectively overseeing hundreds of chapters across every state and territory. While these clubs have long been the target of police attention, especially for their suspected involvement in organised crime, recent high-profile events in Sydney involving the murder or attempted murder of OMCG members (alongside other criminal gang members) have once again drawn attention to the impact of conflict within and between rival clubs.

As these events illustrate, OMCGs have not always grown, spread or co-existed peacefully, and competition between them has sometimes become violent. In the last few decades OMCGs have become synonymous with organised crime. Individuals who are affiliated with an OMCG have increasingly taken part in the trafficking of drugs and other illicit commodities (Morgan, Dowling & Voce 2020; von Lampe & Blokland 2020), regularly

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facilitated by the structure and resources of their clubs (Dowling et al. 2021). The more recent growth and spread of OMCGs has been partially attributed to the desire to exploit new illicit markets, and weak legislative or policing regimes (Dowling & Morgan 2021; McNab 2013). Consequently, disputes have sometimes emerged between clubs as they compete for control of the territories or resources required to generate illicit profit (Monterosso 2018; Quinn & Forsyth 2011). Indeed, clubs showing evidence of organised crime involvement are also more likely to have affiliates with recorded violence and intimidation offences, hinting at the role of violence as an enabler of illicit enterprises (Morgan, Dowling & Voce 2021).

However, disputes between OMCGs can also reflect other concerns. OMCGs are characterised by internal cultures that glorify violence and advocate loyalty to the club and its members above all else (McNab 2013; Quinn & Forsyth 2009; Veno 2012). As is the case for street and youth gangs (Decker, Melde & Pyrooz 2013; McGloin & Collins 2015), displays of aggression, especially when carried out to defend or promote the club, contribute to enhancing affiliates' reputations and status, and consolidating bonds with other members (Dowling et al. 2021; Lauchs, Bain & Bell 2015; Quinn & Forsyth 2011, 2009). Similarly, club chapters preside over defined areas and defend these areas fiercely. A club's perceived power often equates to the territory they control, and territorial violations are regularly treated as an attack on that club's reputation and honour. Finally, a number of OMCGs have longstanding rivalries with other clubs, stemming from disputes between founding or prominent members (Sanderson, Bell & Merrington 2014), ongoing struggles for influence and dominance (Gorrey & Inman 2018), or historical grievances, including where breakaways from existing clubs have formed new clubs or joined others (Knowles 2018).

While isolated acts of aggression between affiliates of different OMCGs are relatively common, disputes have sometimes escalated into 'wars' between clubs, involving coordinated, sustained and repeated acts of violence. The targets of violence during these conflicts are often other OMCG affiliates or their property, although attacks regularly spill over into public places, spreading fear and sometimes causing harm to others (eg Dowling et al. 2021; Quinn & Forsyth 2011).

While there are abundant anecdotal, ethnographic and case study accounts of these conflicts, little research to date has quantitatively examined the patterns of offending among OMCG affiliates in the lead-up to and during these conflicts, including changes in the frequency and concentration of offending in conflict zones. Indeed, few studies have examined spatial patterns of offending and criminal mobility among OMCG affiliates in Australia generally. Emerging Australian research has revealed patterns in the criminal mobility of OMCG members across states and territories (Dowling & Morgan 2021), as well as the spatial concentration of offending at a local level (Lakeman, Benier & Wickes 2021), but this research does not specifically examine how these offending patterns relate to club conflict.

There is, however, a substantial body of high-quality evidence on the implications of territorial conflict between other types of gangs, especially those operating in North America. This research has demonstrated that gang rivalries influence the distribution of violence in a community (Tita & Radil 2011; Valasik & Tita 2018), that inter-gang violence clusters around the boundaries of gang territories (Brantingham et al. 2012), and that inter-gang violence also triggers increases in crimes unrelated to the conflict (Brantingham, Yuan & Herz 2021). While there are important differences between these gangs and OMCGs, there are similarities with respect to the importance of territory, the presence of rivalries, and the symbolic value of violence (von Lampe & Blokland 2020), and these international studies suggest variations in recorded offending are likely during conflicts between OMCGs.

A greater understanding of how offending by OMCG affiliates may change during inter-club conflicts will add to the limited literature on the spatial concentration and criminal mobility of OMCGs in Australia, and build on the crime and place literature, with particular reference to conflict between clubs. It will also help police to anticipate and better respond to changes in the offending of OMCG affiliates at the onset of conflicts.

Methodology

This research examined the impact of conflict between OMCGs on the prevalence and spatial distribution of recorded offending. We analysed the recorded offending of two clubs that were in conflict between 2016 and 2018. We compared this to the recorded offending of OMCGs not involved in the conflict in the same time period and regions. This research addresses the following questions:

- Were there changes in the spatial distribution of recorded offences committed by affiliates of conflict OMCGs during the conflict?
- Were there changes in the prevalence of recorded offending among conflict OMCGs during the conflict?

Data

A data extract was taken from the Computerised Operational Policing System of the New South Wales Police Force (NSWPF) for 5,512 individuals affiliated with 26 OMCGs. These data featured 143,497 offences for which these individuals had been proceeded against between January 1998 and February 2020, and included descriptions of each offence and details such as date, suburb, local government area (LGA) and criminal justice outcomes. This dataset was linked with an extract of information from the NSWPF Gangs database. This database contains details such as the rank and club affiliation of individual OMCG affiliates. Data were linked using central names index numbers of the NSWPF, creating a de-identified record of offences committed by OMCG affiliates across this time period.

Analytic strategy

This research focused on a territorial conflict between two OMCGs in New South Wales between 2016 and 2018. Information on this conflict, including its duration, participants and the disputed territory, was provided in confidence by NSWPF. The ‘conflict period’ extended from late 2016 to mid-2018, a period of approximately 19 months. For this analysis, we considered the 12 months after the onset of the conflict to examine immediate changes in recorded offending among these OMCGs. This period was also selected to limit the influence of intensified policing approaches during the conflict. We refer to three periods throughout this analysis:

- the pre-conflict period—January 2010 to October 2016;
- the conflict period—the 12 months from November 2016 to October 2017; and
- the entire period—January 2010 to October 2017.

The ‘conflict region’ was defined by the boundaries of the LGA in which the territorial dispute between the two clubs occurred. This region was identified in consultation with the NSWPF. We then operationalised a geographic ‘spillover region’ for analysis, which consisted of all LGAs immediately bordering the conflict region. There was no evidence of any other territorial conflict between OMCGs in either the conflict region or spillover region during the study period. The remaining LGAs in New South Wales were also aggregated for analysis. Due to the sensitivity of the data used for this analysis, and the likelihood of re-identification if both the time period and the geographic characteristics of the location were reported, we de-identified the location for analysis.

We limited the analysis to offence types that are believed to reflect conflict-related activities, based on prior research examining conflicts between OMCGs (Dowling et al. 2021; McNab 2013; Monterosso 2018; Quinn & Forsyth 2011, 2009; Veno 2012), along with information about notable incidents during the conflict period provided by NSWPF. They included offences that may reflect acts of aggression between clubs, including violent offences, threats, blackmail and extortion, weapon use and possession offences, public order, property damage and serious driving offences. Other offence types unlikely to be involved in club conflict such as burglary and theft offences, sexual offences and fraud offences were excluded, as were offences relating to criminal justice activity, such as breach offences (with the exception of a sensitivity analysis that examined changes in overall offending within the conflict region by clubs involved in the conflict).

We begin with a descriptive analysis of offences before and during the conflict period. This is followed by an analysis of broader geospatial changes in recorded offending by affiliates of these two OMCGs that occurred following the onset of this conflict. The final stage involved comparing actual and forecast crime for clubs involved in the conflict, as well as for other clubs.

Geospatial analysis

The haversine formula, which measures the distance between two points on a sphere (Chopde & Nichat 2013), was used to measure the distance between the suburb in which each offence was committed and the central point of the conflict region (the centroid). Distances calculated with this formula were analysed using k-means, an unsupervised, centroid-based clustering algorithm that is useful in identifying independent clusters by measuring distance in feature space (Bora & Gupta 2014). This was used to identify latent clusters of offences with common distances from the centre point of the conflict region. Measuring the distance and clusters prior to and during the conflict period provides insight into the geospatial distribution of offences and whether certain clusters of offences were attracted to the conflict region during the conflict period. We used standardised data to account for differences in the magnitude of distances produced after applying the haversine formula, with some offences very close to the conflict region, and some far away.

The k-means algorithm functions by randomly selecting a centroid and iteratively assigning similar data points to develop clusters (Amer 2020). Once all data points have been assigned to these clusters, the k-means algorithm recomputes the centroid to best fit the clusters by computing the mean distance between all data points within each cluster and assigning that point as the new centroid (Amer 2020). This process is repeated until the centroids of new clusters do not change or all data points remain in the same cluster (Amer 2020; Jain & Dubes 1988).

The optimal number of clusters was identified using the silhouette method, which provides two coefficients that can be used to evaluate the quality of latent clusters (Batool & Hennig 2021). The silhouette coefficient is first used to evaluate the fit of individual clusters by how well these clusters are separated from the others (Anitha & Patil 2019). The mean silhouette coefficient describes the global mean of clusters and is used to identify the overall validity of clustering in the model (Lengyel & Botta-Dukát 2019). These coefficients typically fall between −1 and 1 (Lleti et al. 2004). A negative coefficient or coefficient close to zero suggests low confidence in the clustering, while a positive coefficient closer to 1 indicates more accurate clustering. Using the silhouette coefficients to optimise the number of clusters and minimise within-cluster outliers helps mitigate the limitations of relying on the Euclidean distance, which is a feature of the k-means algorithm and which can negatively impact evaluation metrics (Raykov et al. 2016).

After assessing cluster quality, two simple measures relating to geospatial distance were considered:

- the mean distance between all offences and the centre point of the conflict region in the pre-conflict and conflict periods; and
- the mean distance between offences within each cluster and the centre point of the conflict region.

Analysis was performed using the statistical analysis software R and the 'dplyr', 'cluster' and 'factoextra' packages.

Temporal analysis

To supplement analysis of geospatial changes in offending by these two clubs, three auto-regressive integrated moving average (ARIMA) models were computed to consider offending across time. In this study, observed monthly offence counts during the conflict period were compared with counts that were forecast based on historical (ie pre-conflict) data. This synthetic counterfactual allowed us to examine whether the onset of the conflict precipitated a change in recorded offending compared with what would have been expected had there been no conflict.

Generating an ARIMA model involves assessing whether data transformation or differencing is required to account for non-stationarity (variation in the statistical properties of a time series dataset over time) and selecting the autoregressive (AR) and moving average (MA) model parameters required to account for autocorrelation and partial autocorrelation (ie the correlation of a time series dataset with lags of itself). Where seasonality is detected, additional seasonal differencing, AR and MA parameters are included. Model selection in this study was facilitated by an automatic search algorithm developed by Hyndman and Khandakar (2008). This algorithm compares successive ARIMA models and identifies the best fitting model based on the corrected Akaike information criterion (AICc). Model selection was aided by visual inspection of the time series data, and the autocorrelation and partial autocorrelation function plots. The mean absolute scaled error is provided for each ARIMA model, which measures the accuracy of ARIMA forecasts by comparing them to a naïve model. A naïve model is generated by equating the current forecast to the output from the step immediately prior, without considering seasonality (Hyndman & Koehler 2006). A mean absolute scaled error value greater than 1 suggests that ARIMA forecasts have performed poorly, while a value below 1 suggests an accurate model compared to the naïve model (Franses 2016; Hyndman & Koehler 2006). Follow-up Ljung–Box testing was undertaken post-model estimation to ensure that there was no remaining autocorrelation in model residuals.

Four ARIMA models were developed for the conflict region, the spillover region, and for the rest of New South Wales. In estimating these models, the offence counts for both clubs from January 2010 until the conflict began at the end of October 2016 were used to forecast recorded offending for the conflict period, along with 95 percent confidence intervals. We then compared the observed offence counts for the conflict period to the forecasted point estimates for the same period. We can conclude the number of offences has increased or decreased when the observed value falls outside the upper or lower bound of the 95 percent confidence interval. Modelling was performed using statistical analysis software R, and the 'ggplot2' and the 'forecast' packages.

Limitations

Given the reliance on data relating to offences that resulted in some legal action by police, we cannot account for offences that were not known to law enforcement. Additionally, given OMCG affiliates are a visible group, there is a risk that the results are influenced by proactive policing activity, especially during the conflict. However, we attempted to mitigate this risk by focusing on offence types most likely to relate to club conflict, and by comparing changes in recorded offending by the clubs in conflict to that of clubs that were not involved in the conflict. Further, there may be a lack of precision with the exact dates of the conflict, identified from police intelligence, which may have commenced earlier than we are aware. Finally, the relevance of this analysis to other club conflicts, or conflicts in other jurisdictions, requires further consideration. The results presented in this paper are not applicable to other offending populations, especially those that do not have such frequent contact with the criminal justice system (see Morgan, Dowling & Voce 2020).

Results

The number of offences involving OMCG affiliates in the three regions of interest is presented in Table 1. From 2010 until the end of the conflict, 9,267 offences were attributed to affiliates of 26 OMCGs across New South Wales, of which 22 percent—or 2,022 offences—were attributed to the clubs in conflict. Within the conflict region, 1,165 offences were attributed to 23 clubs. Twenty-seven percent of these offences—312 offences—were attributed to the two clubs involved in the conflict. Counts of recorded offending were also calculated for the spillover region, consisting of LGAs that immediately border the conflict region. The proportion of offences committed by these two clubs in the conflict (32%) and spillover (10%) regions increased during the conflict period relative to the pre-conflict period (12% & 9%, respectively). The mean number of offences per month involving the conflict OMCGS also doubled (from 3.01 to 8.41 offences per month). Meanwhile, the proportion of their overall recorded offending that occurred outside the conflict and spillover regions (ie in the rest of New South Wales) also dropped sharply from 79 percent to 58 percent.

Table 1: Proportion and number of offences by OMCG affiliates, by time period and region

		Conflict region % (total *n*; mean monthly offences)	Spillover region % (total *n*; mean monthly offences)	Rest of NSW % (total *n*; mean monthly offences)
Entire period	Conflict OMCGS (*n*=2,022)	15 (312; 3.32)	9 (177; 1.88)	76 (1,533; 16.31)
	Non-conflict OMCGS (*n*=7,245)	12 (853; 9.07)	13 (916; 9.74)	75 (5,476; 58.26)
Pre-conflict period	Conflict OMCGS (*n*=1,705)	12 (211; 2.6)	9 (146; 1.78)	79 (1,348; 16.44)
	Non-conflict OMCGS (*n*=6,312)	11 (682; 8.32)	12 (764; 9.32)	77 (4,866; 59.34)
Conflict period	Conflict OMCGS (*n*=317)	32 (101; 8.41)	10 (31; 2.58)	58 (185; 15.42)
	Non-conflict OMCGS (*n*=933)	18 (171; 14.33)	16 (152; 12.67)	66 (610; 50.83)

Note: The pre-conflict period refers to January 2010 to October 2016, the conflict period refers to the 12 months from November 2016 to October 2017, and the entire period refers to January 2010 to October 2017

Source: NSW OMCG offending database [computer file]

The number and proportion of affiliates with at least one offence in each region is presented in Table 2. Within the observation period, offending patterns do not generally indicate a significant degree of criminal mobility across the three regions. Only five percent of criminally active affiliates of the two clubs involved in the conflict had offences recorded across more than one of the three regions, suggesting that there was little movement into the conflict or spillover regions with the onset of the conflict. The OMCGs that were not involved in the conflict featured a similarly low rate of criminal mobility after the onset of the conflict.

Table 2: Proportion and number of OMCG affiliates who committed at least one offence, by time period and region

		Conflict region % (*n*)	Spillover region % (*n*)	Rest of NSW % (*n*)	Criminally active affiliates who were criminally mobile %
Entire period	Conflict OMCGS (*n*=685)	21 (144)	12 (84)	79 (539)	12
	Non-conflict OMCGS (*n*=2,244)	16 (368)	19 (426)	84 (1877)	19
Pre-conflict period	Conflict OMCGS (*n*=604)	15 (102)	10 68)	81 (488)	10
	Non-conflict OMCGS (*n*=2,109)	15 (310)	18 (388)	84 (1,772)	17
Conflict period	Conflict OMCGS (*n*=198)	35 (69)	11 (21)	59 (117)	5
	Non-conflict OMCGS (*n*=573)	20 (113)	13 (74)	70 (399)	3

Note: The proportion of affiliates in each time period was calculated using the number of criminally active affiliates within each time period

Source: NSW OMCG offending database [computer file]

Geospatial analysis

During the period of conflict, the geographic distribution of recorded offending was closer to the conflict region. Table 3 provides the mean geographic distance between offences and the centre point of the conflict region along with the evaluation metrics for the k-means clustering algorithm. The mean silhouette coefficient for each model, and silhouette coefficients for each cluster within these models, show that data were effectively separated into independent clusters. As Table 3 shows, the overall mean distance from the conflict region reduced after the onset of the conflict, by around 36 kilometres (from 149.54 km to 113.07 km). During the conflict, the cluster of offences closest to the centre of the conflict region was markedly closer than pre-conflict (11.95 km vs 13.07 km). As well as the mean geographic difference being significantly lower, the cluster of offences nearest the centre of the conflict region also accounted for a much greater proportion of total offences during the conflict period than in the pre-conflict period (27% vs 10%). Together, these findings suggest an increased amount of offending by OMCG affiliates in and around the conflict region. However, further analysis is needed to verify this conclusion.

Table 3: Mean geographic distance between offences and the centre point of the conflict region and evaluation metrics for k-means

Period	Clusters	Offences by affiliates of conflict OMCGs (*n*)	Proportion of total offences within this cluster	Mean distance between offences and centre of conflict region in km (range)	Silhouette coefficient
Pre-conflict period	Cluster 1	172	10%	13.07 (0.22 – 33.47)	0.74
	Cluster 2	123	7%	60.15 (38.83 – 80.11)	0.67
	Cluster 3	974	58%	127.72 (97.56 – 157.49)	0.81
	Cluster 4	243	14%	194.67 (159.31 – 255.51)	0.63
	Cluster 5	126	7%	322.20 (260.55 – 396.20)	0.82
	Cluster 6	67	4%	500.48 (409.13 – 601.12)	0.65
	Model	1,705		149.54[a] (0.22–601.12)	0.75
Conflict period	Cluster 1	84	27%	11.95 (0.22 – 28.96)	0.71
	Cluster 2	39	12%	51.93 (29.85 – 71.90)	0.50
	Cluster 3	139	44%	125.69 (111.72 – 160.83)	0.86
	Cluster 4	30	9%	203.97 (162.33 – 242.05)	0.75
	Cluster 5	14	4%	325.25 (361.06 – 376.62)	0.41
	Cluster 6	11	4%	479.87 (472.64 – 511.63)	0.95
	Model	317		113.07[a] (0.22–511.63)	0.75[b]

a: Mean distances between all offences in the model and the centre point of the conflict region

b: Mean silhouette coefficient

Note: Analysis is limited to the two clubs involved in the conflict

Source: NSW OMCG offending database [computer file]

Temporal analysis

Table 4 provides the parameters for the ARIMA models developed for the conflict region, the spillover region and the rest of New South Wales. Models were developed for both the conflict and non-conflict clubs. While there was volatility in recorded offending across each region, the accuracy of the models was acceptable. Results indicate that, during the conflict period, recorded offending exceeded the ARIMA forecast among both clubs that were involved in the conflict and those that were not.

Table 4: ARIMA model parameters

	Conflict clubs			Non-conflict clubs		
	Conflict region ARIMA (1,0,0)	Spillover region ARIMA (1,0,0)	Rest of NSW ARIMA (0,0,1)	Conflict region ARIMA (0,1,1)	Spillover region ARIMA (0,0,0) (0,0,1)	Rest of NSW ARIMA (0,0,0) (1,0,0)
AR coefficient	0.349 (0.146 – 0.552)	0.044 (−0.172 – 0.261)				
MA coefficient			0.108 (−0.095 – 0.310)	−0.905 (−1.017 – −0.792)		
SMA coefficient					0.189 (−0.048 – 0.427)	
SAR coefficient						0.178 (−0.04 – 0.397)
AICc	375.04	347.07	540.77	501.28	485.66	674.27
Log-likelihood	−184.52	−170.54	−267.38	−248.56	−239.67	−333.98
Mean absolute scaled error	0.71	0.81	0.76	0.63	0.79	0.71
Ljung–Box χ^2	23.45	6.70	10.88	12.84	14.04	13.82
No. months exceeding forecast	10	5	5	9	6	2
No. months exceeding upper 95% forecast bound	5	1	1	3	2	0

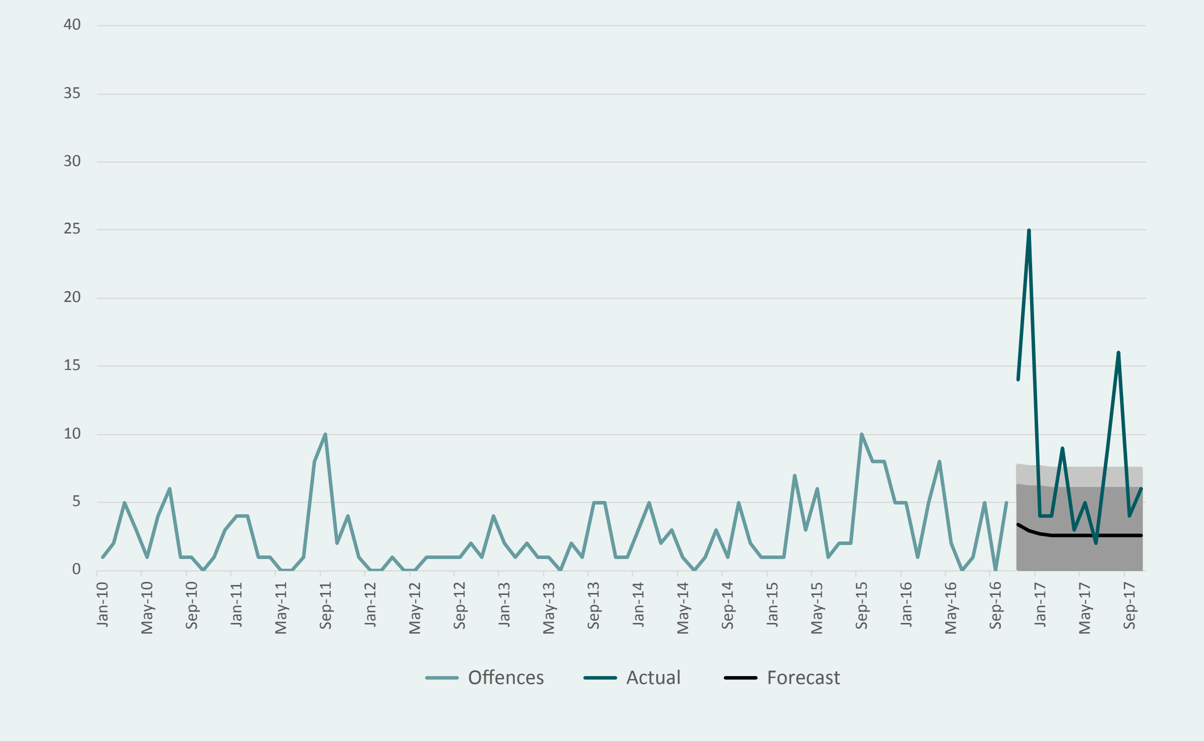
Note: AR=autoregressive parameter. MA=moving average parameter. SMA=seasonal moving average parameter. SAR=seasonal autoregressive parameter. AICc=corrected Akaike information criterion

Source: NSW OMCG offending database [computer file]

Figure 1 details the ARIMA forecast for recorded offences within the conflict region by the clubs in conflict. The model featured low but still acceptable accuracy, likely due to the small number of offences and volatility in the pre-conflict period. There were five months during the conflict period where the number of offences was outside of the 95 percent confidence interval for the forecast. Overall, when the predicted and actual number of offences were compared, there were an estimated 65 additional recorded offences involving the clubs in conflict during the conflict period. It was clear that recorded offences were most concentrated at the onset of the conflict.

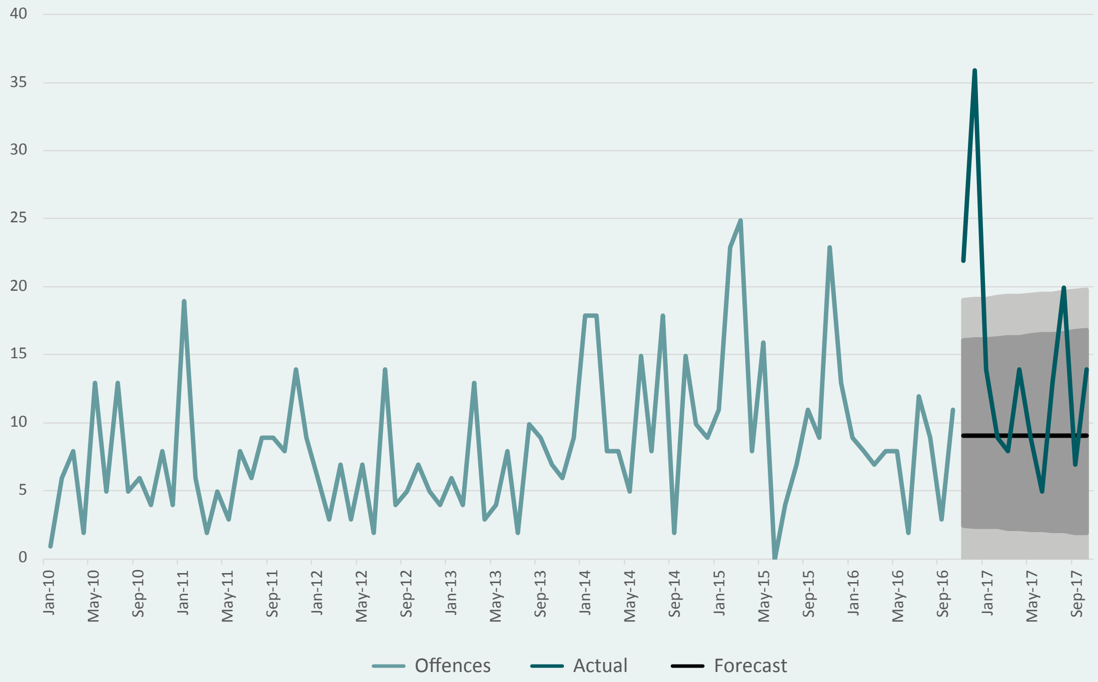
Figure 2 details the ARIMA forecast for offences by all other clubs within the conflict region. When the predicted and actual number of offences were compared, there were an estimated 63 additional offences involving non-conflict clubs during the conflict period. However, there were three times as many offences in the pre-conflict period by non-conflict clubs, meaning this was proportionally a much smaller increase than among conflict clubs. Further, most of this increase occurred early in the conflict period. That this initial increase was observed among both conflict and non-conflict clubs suggests it might be partly explained by increased law enforcement activity. It may also reflect a general unrest in the local biker milieu.

Figure 1: ARIMA model for recorded offences by both conflict clubs in the conflict region, January 2010 to October 2017



Note: Light grey shading indicates 95% confidence intervals for forecasted trend. Dark grey shading indicates 85% confidence intervals
Source: NSW OMCG offending database [computer file]

Figure 2: ARIMA model for offences by non-conflict clubs in the conflict region, January 2010 to October 2017

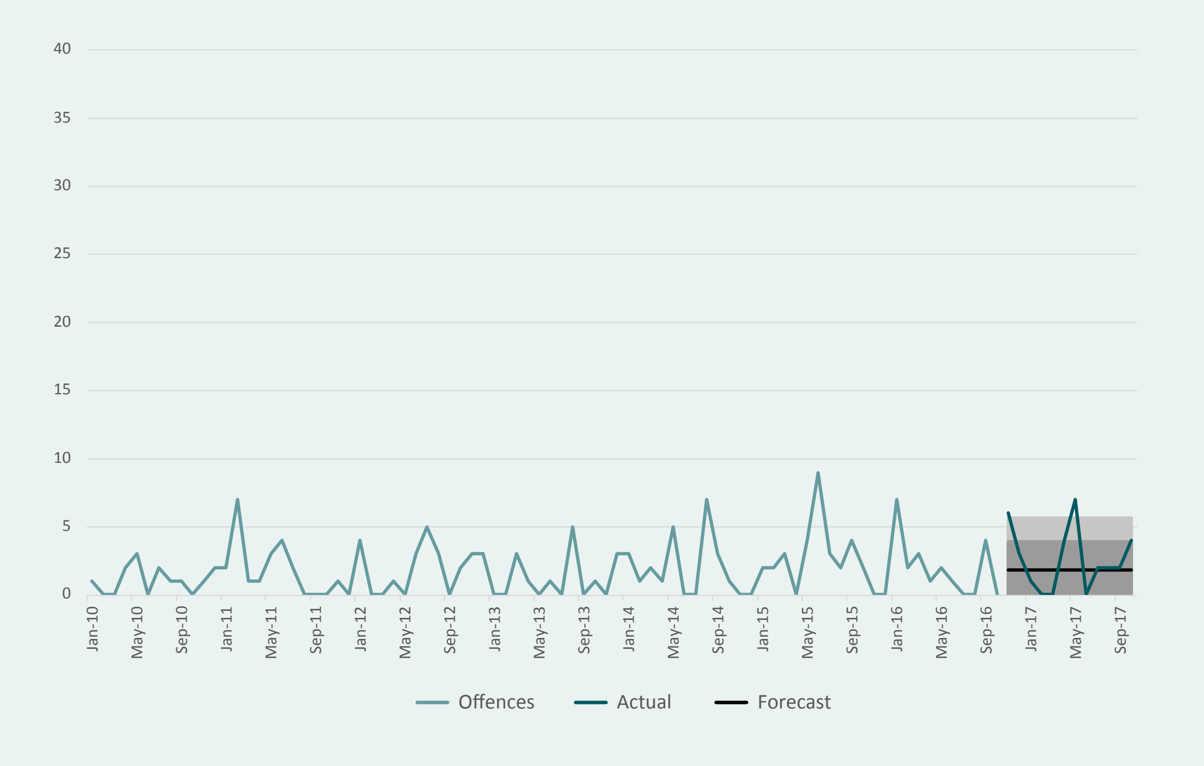


Note: Light grey shading indicates 95% confidence intervals for forecasted trend. Dark grey shading indicates 85% confidence intervals
Source: NSW OMCG offending database [computer file]

As an additional sensitivity analysis, and to address the question of whether we were measuring an enforcement effect, we separately computed an ARIMA model for both of the conflict clubs using all recorded offences within the conflict region across the same time frame, rather than restricting the analysis to conflict-related offences only. This model did not demonstrate the same degree of volatility in offending during the forecast period, with only one month that exceeded the 95 percent confidence interval for the forecast (see *Appendix*). This is important, because if the observed changes in recorded offending for conflict-related offences were entirely the result of increased enforcement, then we would expect to see an equal or greater increase in these other recorded offences, many of which are related to policing activity (eg drug offences and justice-related offences).

Figure 3 details the ARIMA model for recorded offences by conflict clubs in the LGAs that immediately border the conflict region. There were very few offences by these clubs within the spillover region throughout the observation period, suggesting that changes in recorded offending may have been localised to the region of the conflict. There was similarly very little evidence of an increase in recorded offending by non-conflict clubs in the spillover region (see Table 4).

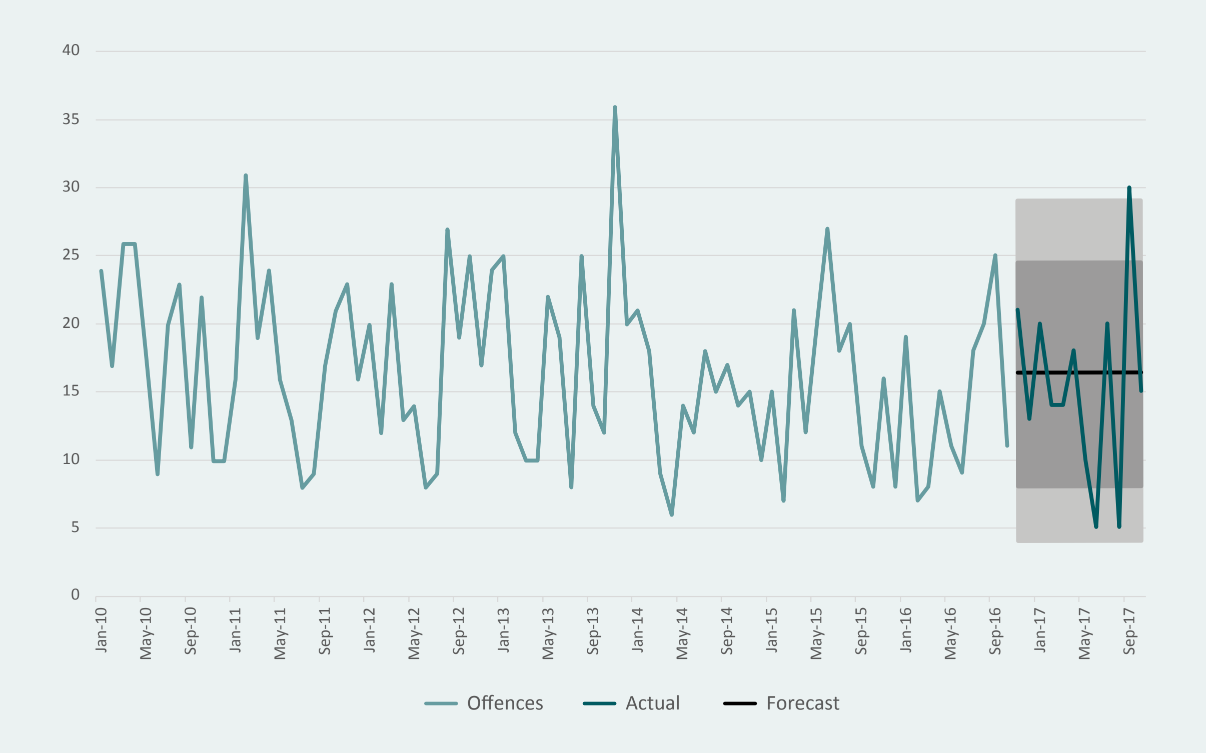
Figure 3: ARIMA model for offences by both conflict clubs in the spillover region



Note: Light grey shading indicates 95% confidence intervals for forecasted trend. Dark grey shading indicates 85% confidence intervals
Source: NSW OMCG offending database [computer file]

Finally, Figure 4 details the ARIMA model for offences by the clubs in conflict across the rest of New South Wales. Offence numbers during the conflict period were within the 95 percent confidence interval of the forecast for all but one month (which occurred towards the end of the conflict period). Similarly, as shown in Table 4, there was no significant change in recorded offending by non-conflict clubs across the rest of New South Wales, indicating there was no general increase in OMCG-related crime.

Figure 4: ARIMA model for offences by both conflict clubs across NSW, excluding conflict and spillover regions



Note: Light grey shading indicates 95% confidence intervals for forecasted trend. Dark grey shading indicates 85% confidence intervals
Source: NSW OMCG offending database [computer file]

Discussion

This study examines changes in recorded offending by Australian OMCG affiliates at the onset of a territorial conflict between two clubs in the state of New South Wales. Results show a decrease in the mean geographic distance between offences by affiliates of the clubs involved in the conflict and the centre point of the conflict region. Further, there was an increase in recorded offending by those affiliated with the OMCGs involved in the conflict and based in the conflict region. Comparable increases in recorded offending by these individuals were not detected in the areas surrounding the conflict region or across the rest of New South Wales, and there was little mobility into the conflict region by those outside of it. Additionally, while there was an initial increase in recorded offending by affiliates of other OMCGs in the conflict region at the onset of the conflict, these increases were proportionally smaller than those observed among the clubs in the conflict. We did not observe an increase in other offences likely to be unrelated to club conflict, which are more likely to be related to policing activity, suggesting that the observed changes in recorded offending were not entirely the result of police enforcement activity. In short, there were important changes in OMCG-related crime during a period of conflict between two clubs. These changes were largely limited to the clubs involved in the conflict and localised to the territory in dispute.

This study is, to the authors' knowledge, the first to quantify the intensification of criminal activity by OMCG affiliates during an inter-club conflict compared with a pre-conflict period and benchmarked against the recorded offending patterns of other OMCG affiliates not involved in the conflict. These findings add to the emerging literature on spatial concentrations of offending and criminal mobility among OMCGs in Australia (Dowling & Morgan 2021; Lakeman, Benier & Wickes 2021). They also lend further weight to the already numerous accounts of such intensifications reported in the literature (eg Dowling et al. 2021; Quinn & Forsyth 2011), and are consistent with the findings of international studies showing the impact of gang conflicts on the distribution of crime (Valasik & Tita 2018). More broadly, this study provides some clarity on the changes law enforcement are likely to see in the threat environments they operate within when these conflicts emerge. That these changes appear to be limited to the clubs and areas at the centre of conflicts may assist law enforcement to allocate officers and resources to mitigate the harms associated with these conflicts.

This research analysed recorded offending during a single conflict between two OMCGs. While considering conflict-related offending, we do not further discriminate between types of offending. The extent to which these conclusions can be generalised to other conflicts is limited. OMCGs engage in conflicts for a range of reasons, including for control of illicit commodities, markets or proceeds (Monterosso 2018; Quinn & Forsyth 2011), in defence of club honour and reputation, and revenge (Dowling et al. 2021; Knowles 2018; Lauchs, Bain & Bell 2015; Lauchs & Gilbert 2017; Quinn & Forsyth 2011, 2009; Sanderson, Bell & Merrington 2014). It is also possible that geographic characteristics, such as population density, contributed to the territorial dispute. Whether the limited and localised changes observed in this study hold when examined in relation to non-territorial conflicts, some of which may be more likely to draw in a larger proportion of affiliates across a wider area, remains an important question.

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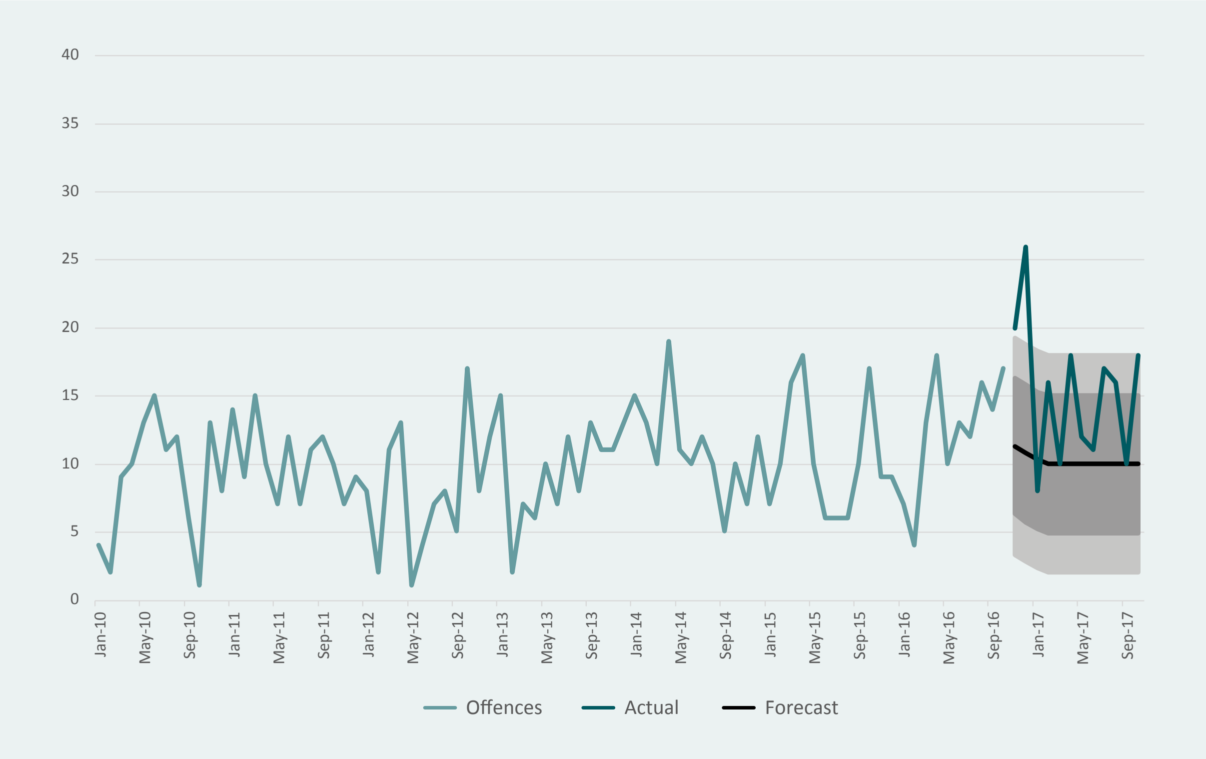
Appendix

Figure A1: ARIMA model for all recorded offences by both conflict clubs in the conflict region



Note: Light grey shading indicates 95% confidence intervals for forecasted trend. Dark grey shading indicates 85% confidence intervals
Source: NSW OMCG offending database [computer file]

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