Long-term forecasting of Knife Crime (Used causing Injury)

Data Analytics Lab

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1 Contents

2 Introduction

This project was requested by Project Guardian and the Director of the West Midlands Violence Reduction Unit (VRU).

The VRU is a collaboration of specialists from local government, health, education, police, and criminal justice who work alongside partner organisations and communities and whose remit is to reduce serious violence.

Project Guardian is the West Midlands Police (WMP) team aligned to the VRU. Both receive funding from the Home Office and the Office of the Police and Crime Commissioner (OPCC).

The purpose of this project is to provide long-term forecasts of knife crime (used causing injury) (between one and five years in advance).

The analysis has been requested to provide an evidence base to aid strategic decisions about the prioritisation of investment from the Home Office and the OPCC in order to reduce knife crime in the West Midlands.

This project is complemented by the Violent Crime forecasting project submitted to the Committee in December 2020, as well as the shorter term predictive work presented earlier last year. Knife crime is a sub-set of violent crime and is of particular concern within the West Midlands.

Knife offences causing injury are a relatively rare event when compared with the volume of violent offending overall. However, the serious harm caused to victims and the long-lasting effects on their families, wider communities as well as offenders suggests this offence type warrants special attention. The VRU Strategic Needs Assessment states that in the West Midlands:

"Violence of all types is high compared to other parts of the country and some kinds, such as knife crime, are showing worryingly steep increases in recent years. In 2019, the West Midlands experienced the biggest annual increase in knife crime of any area in England – up 17% on 2018 (compared to a 7% increase nationally)."[1]

Reducing knife crime is a Force priority and therefore WMP is a committed partner in the VRU which promotes an evidence-based, public health approach to violence reduction. Project Guardian also supports the Force's ambition to Act with Precision, which means responding to identified threat and risk by deploying the right people, in the right place, at the right time.

Intelligence analysts have traditionally identified where knife crime hotspots have occurred historically and consequently resourcing decisions are currently based on analysis of historic crime data (currently augmented by the short-term knife crime predictions app which is in beta testing phase).

The purpose of this project is to build a model which can provide predictions to assist strategic decision making and would most likely provide estimates of the total levels of knife crime over

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[1] West Midlands Violence Reduction Unit Strategic Needs Assessment April 2020 https://westmidlands-vru.org/data-insights/strategic-needs-assessment/

time and possibly identify broad locations, for example at the level of Neighbourhood Policing Units (NPU).

This supports the precision policing model and by sharing the findings with partners in the VRU the Force intends to develop innovative ways of collaborating with partners to tackle complex issues and to build trust with communities.

2.1 Summary of Findings

For forecasting so far into the future, a simple model was found to be the best approach to use.

3 Highlights from the Literature

As will be reminiscent from previous reports, the level of knife crime (used causing injury), consequently referred to as knife crime, has seen a decrease over the period from the early 2000s to circa 2012 and then increased to earlier (higher) levels currently:

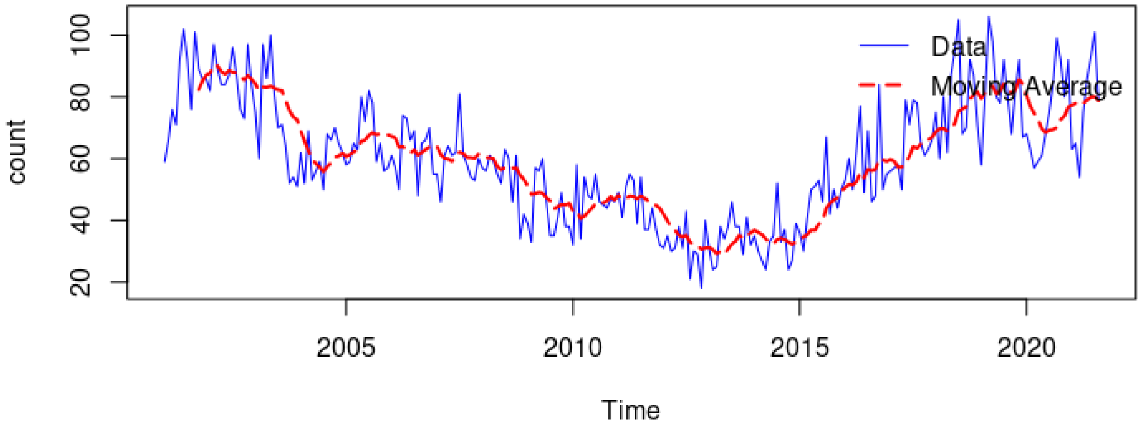


Figure 1: Knife crime over time

It can also be seen from the figure below that these changes result in structural breaks in the time series, so the rise to current levels started at around the back end of 2014 to early 2015:

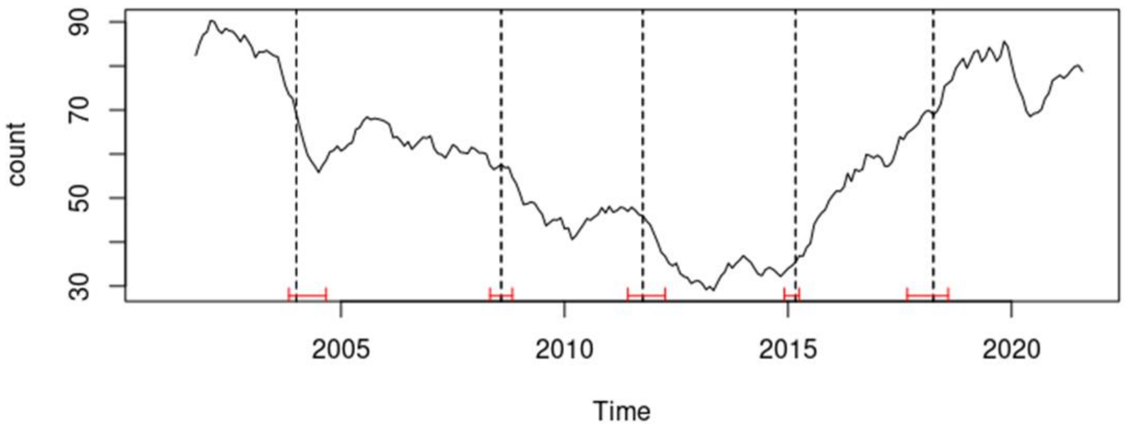


Figure 2: Structural breaks in the time series

This broad pattern of a decline in knife crime towards 2012 and a rise around 2014 / 2015 also appear at the national level:

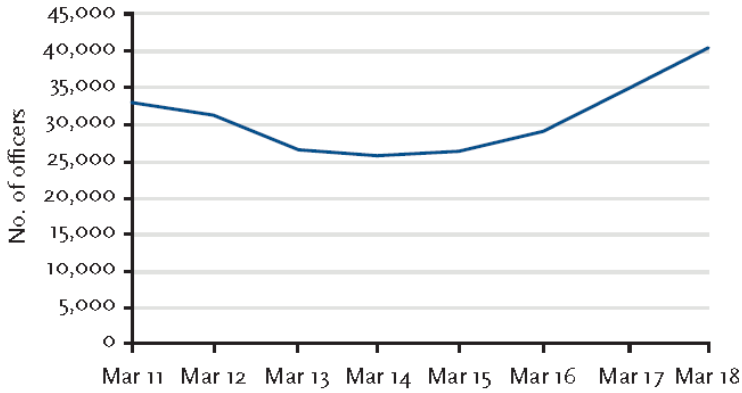


Figure 3: Knife or sharp instrument offences in England and Wales

Source: ONS via Grimshaw and Ford 2018.

This is also reflected to some degree in hospitalization figures for assault by sharp object:

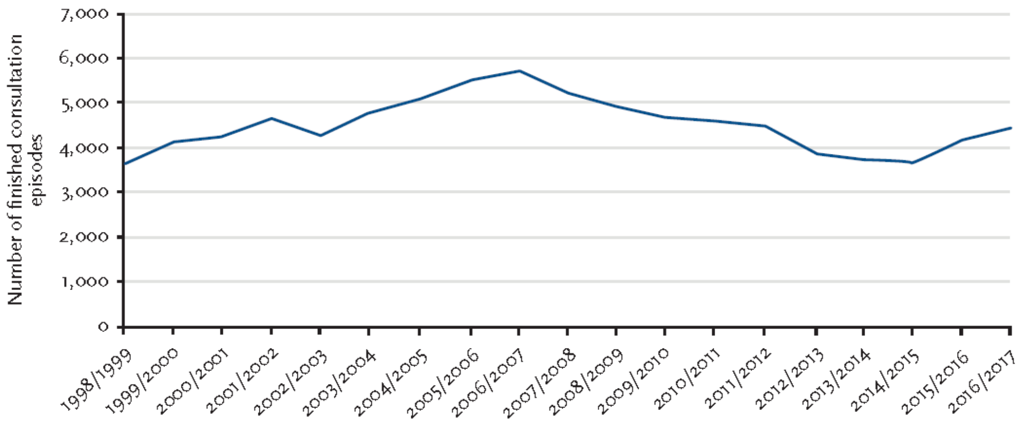


Figure 4: Number of finished consultant episodes for assault by sharp object, England and Wales

Source: Allen and Audickas 2018 via Grimshaw and Ford 2018.

Other, more general knife crimes also generally follow the same pattern:

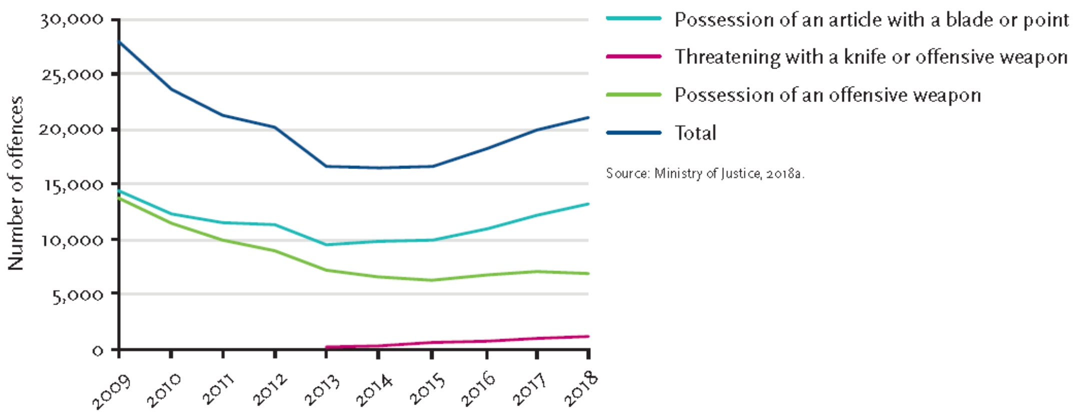


Figure 5: Knife and offensive weapons offences in a caution or conviction, England and Wales

Source: Ministry of Justice 2018 via Grimshaw and Ford 2018.

Sethi et al (2010) noted that overall levels of knife violence as well as increases are driven by the interaction between the characteristics of communities, wider societies, the particular relationships between people and groups and individual level factors. It has also been noted that younger people are responsible for and victims of, the majority of knife crime (Sethi et al 2010, HM Govt. 2018). Income inequality has also been found to correlate positively with levels of violent crime, both with England and internationally (Grimshaw and Ford 2018). The Government's Serious Violence Strategy highlights drugs misuse and county lines as significant direct and indirect factors driving serious violence (HM Government 2018).

A synthesis of the literature (Haylock et al 2020), looking at studies undertaken in the UK, came to similar conclusions in that the studies they examined found positive associations between violent crime and individual circumstances (e.g. (young) age, adverse childhood experiences, poor mental health, previous victimization, poor parental attachment and high risk peer groups) as well as for socio-economic circumstances (e.g. deprivation / high rates of unemployment, high crime levels and economic inequality).

In a review of evidence undertaken for (the then) HMIC, Bradford 2011 concluded that no single study provided robust evidence of a cause and effect relationship between police numbers and crime but taken together pointed to the potential for police numbers to be negatively associated with at least some forms of recorded crime (i.e. more police → less crime of some types, particularly property and acquisitive crime). The evidence for the relationship between police numbers and violent crime was found to be weaker and sometimes contradictory. Bindler and Hjalmarsson 2021 in examining the effects of creating the Metropolitan Police in London in the period 1821 – 1837 (using newly created digitized datasets and utilising a difference-in-differences and pre-post designs) as well as the setting up of police forces over the rest of England and Wales (over the period 1839 – 1856) found that larger forces per capita significantly reduced both violent and property crime.

4 Exploratory Data Analysis and Initial Modelling

A review of the literature highlights many factors, many of them occurring at the level of individuals and some occurring at the societal (socio-economic) level. Given this project aims to produce long-term forecasts of knife crime in the WMP area(s), consideration needs to be made of the potential for explanatory variables that may aid this. It should be noted that individual level variables, whilst they would be suitable for predictive models at the levels of individual nominals, would not be suitable for long-term time series forecasting as they themselves cannot be forecasted.

4.1 Initial modelling

A number of univariate time series models were examined, the best (in terms of the root mean square error (RMSE) and mean absolute error (MAE)) of which are shown below. These models were built on monthly data from 2000 to 2016 and compared to actual data from 2016 to 2021 (so 60 time periods are being forecasted):

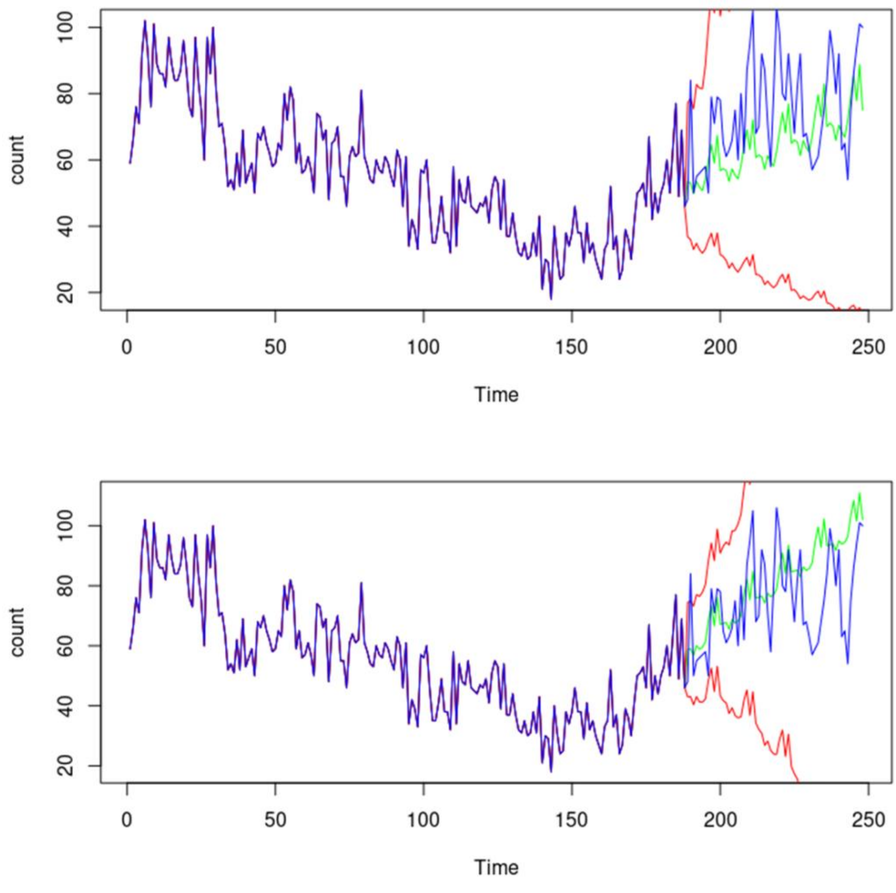


Figure 6: Top - Bayesian state space model on the log of the data; bottom - Bayesian dynamic linear model (green line is central estimate, red lines are 95% credible intervals)

As can be seen from the RMSE measures below, these were the two best performing models over the whole 5 year testing period:

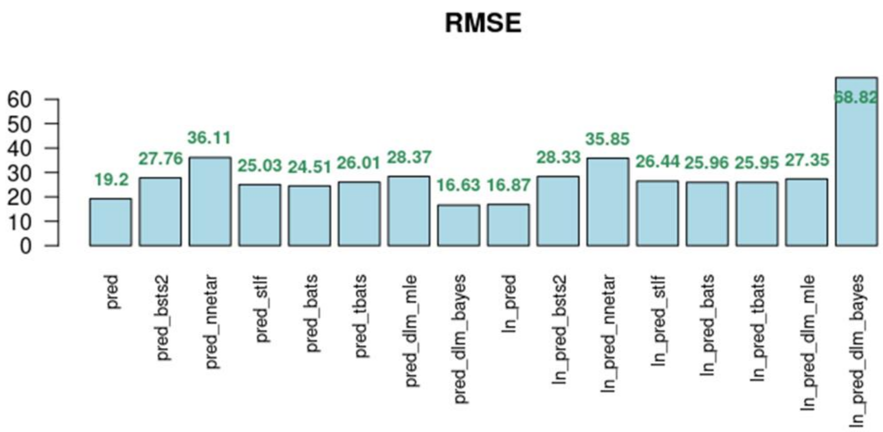


Figure 7: RMSE from several univariate time series models (ln_pred = the model in the top chart in the figure above whilst pred_dlm_bayes = the model in the bottom chart)

As can be seen from the chart below, as would be expected, the further out the forecasts go, then on the whole the greater the RMSE becomes. Whilst the first year or two tend to capture both the trend and the variability, later years tend to capture more the trend and underestimate the variability.

It should be noted that forecasting 60 time periods out is asking a lot of forecasting.

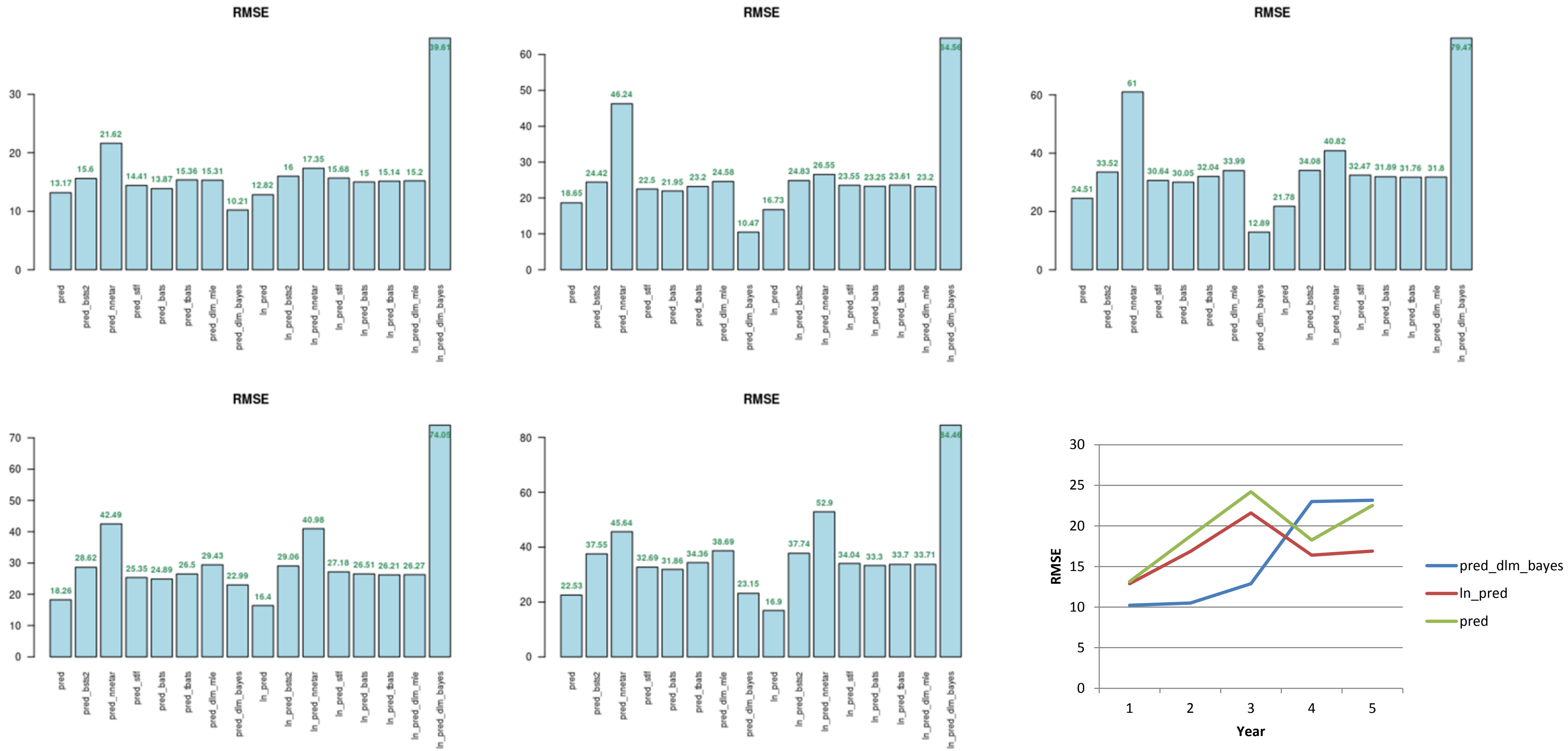


Figure 8: RMSE for years 1 - 5 (each year being forecasts over 12 months)

Due to the difficulty of forecasting over such a long time horizon, two further approaches were also tried. One approach incrementally forecasted for each of the test dataset years, with the forecasts then being used as the training dataset for models forecasting over later years. This approach led to forecasts that were essentially the same as the single Bayesian state space model.

Another approach was to use a two stage model. The first stage uses a forecast of the smoothed time series and a second stage uses the smoothed time series as a feature in a second model with the forecasted smoothed series as a feature for forecasting from the second stage model:

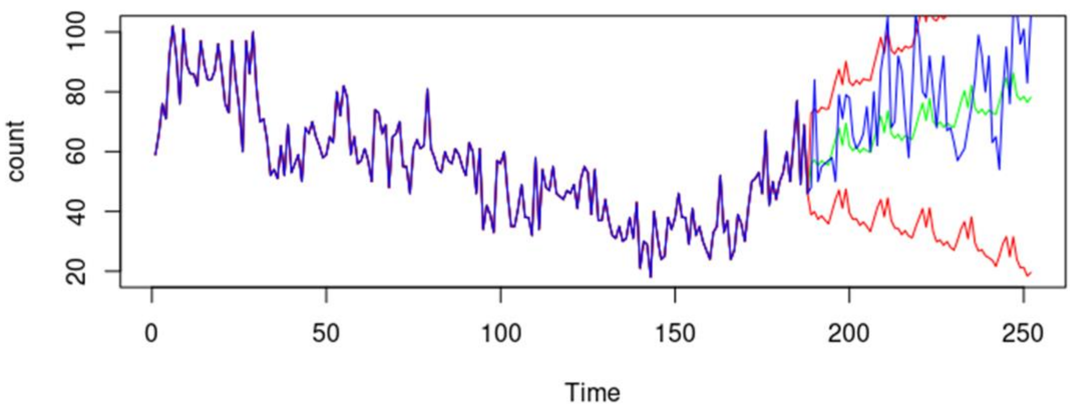


Figure 9: Two stage model forecast for the test dataset period

It can be seen that this approach produces the lowest overall RMSE when compared to the test dataset:

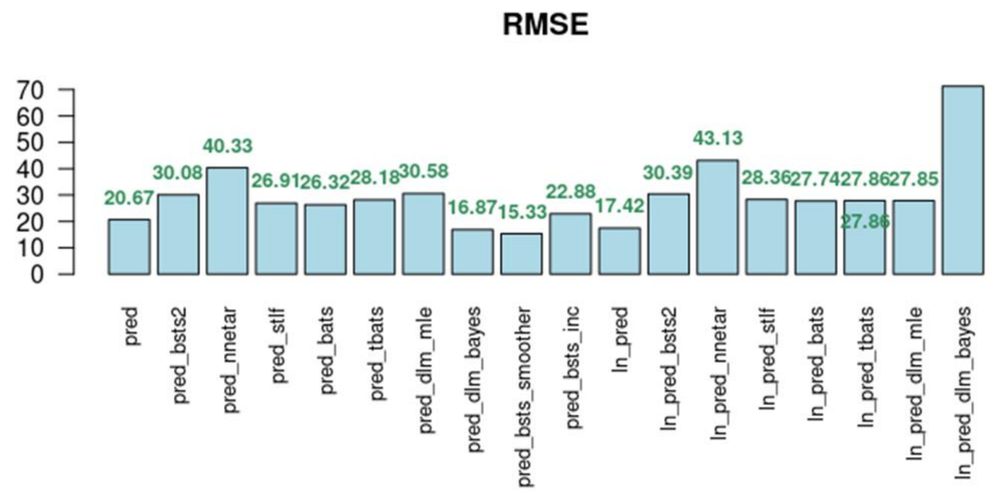


Figure 10: RMSE of the various models including the two stage model (noted as "pred_bsts_smoother")

For each of the years 1 – 5 in the test dataset, the first 3 years are generally better forecasted by the dynamic linear model, but prediction errors are higher for years 4 and 5 (this model essentially seems to place too great a weight on the trend).

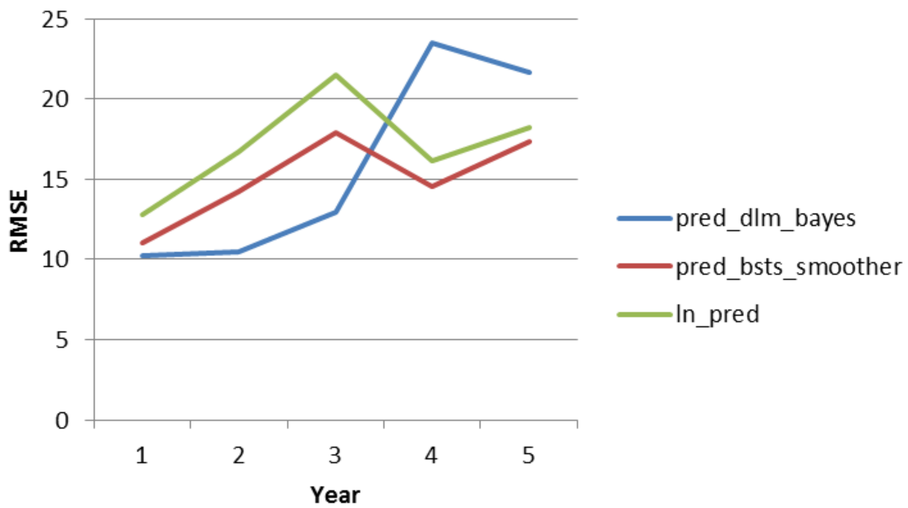


Figure 11: Prediction errors over years 1 - 5 of the top three models

However, when forecasted up until 2027, this model produces unrealistically high forecasts (too great a weight seems to be applied to the latter trend seen in the data).

At the local authority level, it can be seen that Birmingham accounts for the majority of knife crimes (averaging around 32 a month) with many of the other authority areas averaging a lot less at circa 2 – 6 per month.

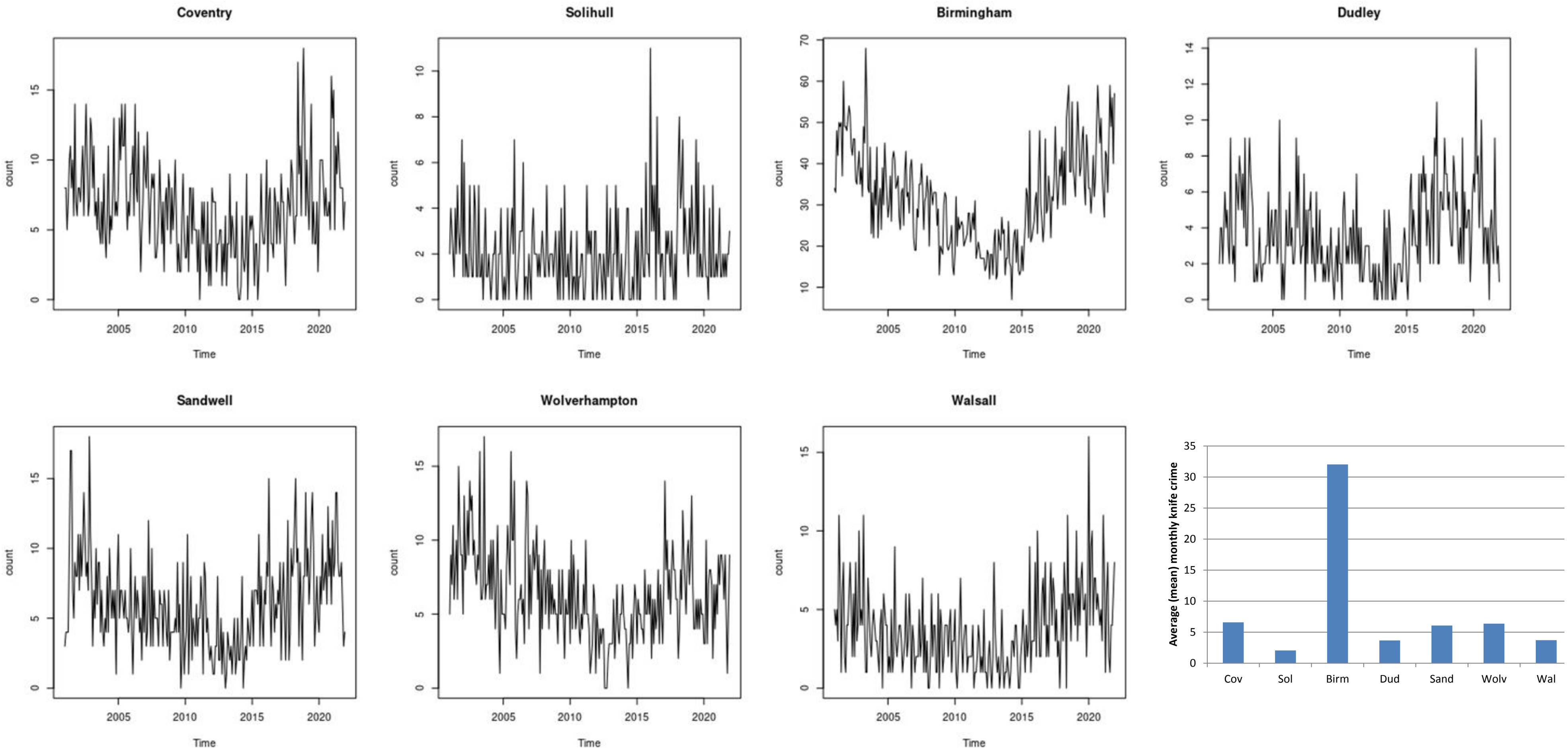


Figure 12: Knife crimes by Local Authority

This also results in in higher variance for the local authorities compared to Birmingham:

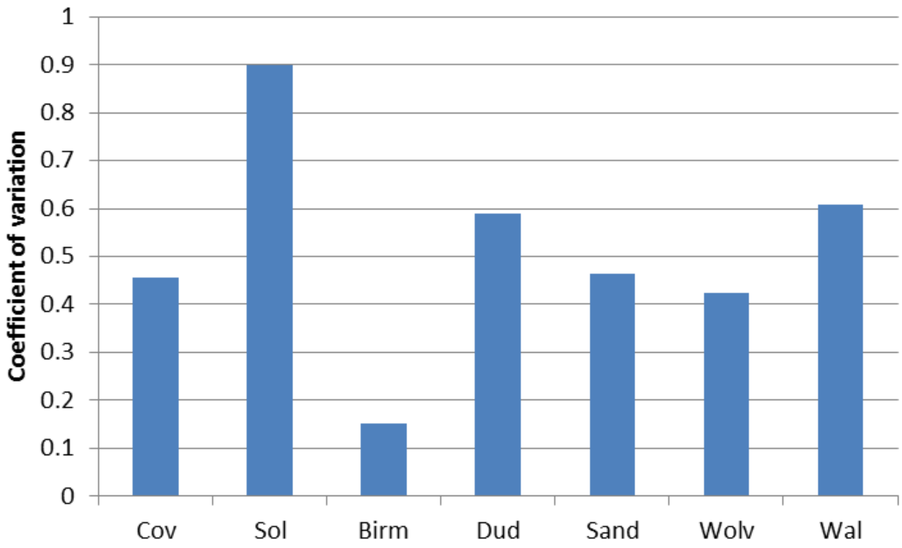


Figure 13: Coefficient of variation of monthly knife crime for the Local Authorities

This means that it would generally be harder to forecast knife crime 60 months (5 years) out for the individual local authorities than for either Birmingham or the WMP area as a whole.

4.2 Other Features

As noted in the literature review a number of other variables appear to be related to knife crime or violent crime more generally. These variables essentially constitute individual or broader socio-economic circumstances.

The relationship between socio-economic variables within the WMP area and knife crime has therefore been examined. It should be noted that the variables that have been examined are those that have data available monthly, so this severely restricts the variables that can be examined.

As can be seen below, the relationship between the rate of unemployment (as measured by the claimant count) does not seem particularly robust with differing periods of increasing and decreasing[2]:

[2] Claimant count (rate) data from NOMIS, CPI inflation rate from Office for National Statistics, GVA Growth from Office for National Statistics.

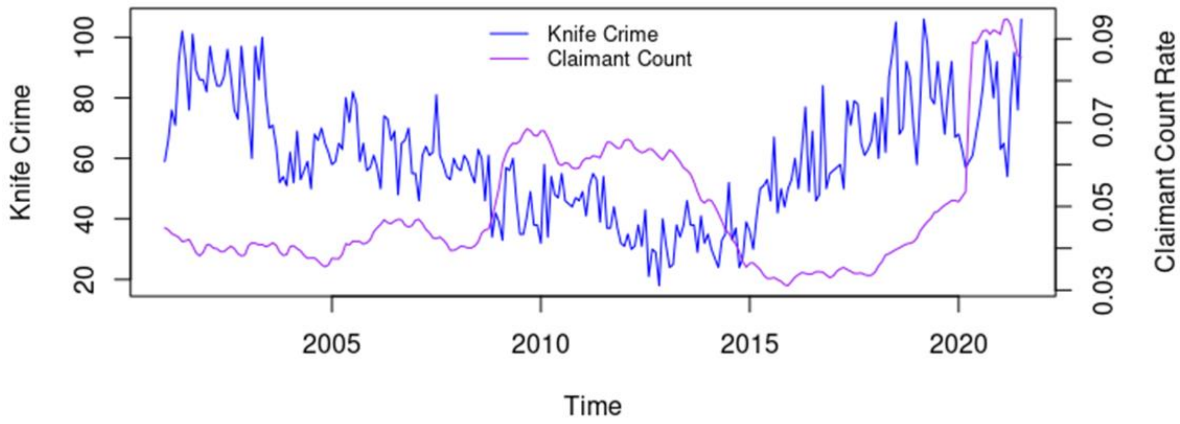


Figure 14: Claimant count and knife crime

There is a negative correlation between the claimant count and knife crime but it is not particularly large (Spearman's rho of -0.25).

As an assessment of the potential utility of using the claimant count as a feature in modelling, Granger causality was examined.

Granger causality essentially models two variables using time lags of both in two models so if:

$A \dashrightarrow B$ but $B -/\rightarrow A$, then A could be said to Granger cause B (but B does not Granger cause A).

Using this analysis, claimant count does not appear to Granger cause knife crime[3].

The relationship between knife crime and inflation also seems less than robust:

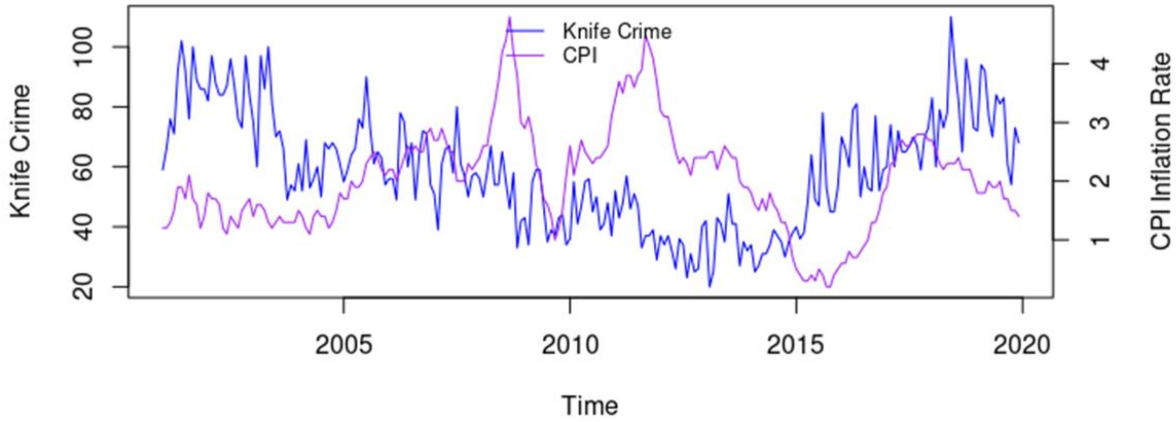


Figure 15: Knife crime and inflation (CPI)

[3] The difference ratio between the Bayesian Information Criterion (BIC) between the two hypotheses of knife crime = knife crime over time v knife crime = knife crime + claimant count is -0.5628; the BIC difference ratio of claimant count = claimant count over time v claimant count = claimant count + knife crime was also shows no Granger causality at -0.02. Checks for stationarity and cointegration were undertaken.

Inflation also does not appear to Granger cause knife crime[4].

The potential relationship between Gross Value Added (GVA) growth and knife crime has also been examined. Because this is growth in GVA, it is difficult to determine from a chart alone the relationship:

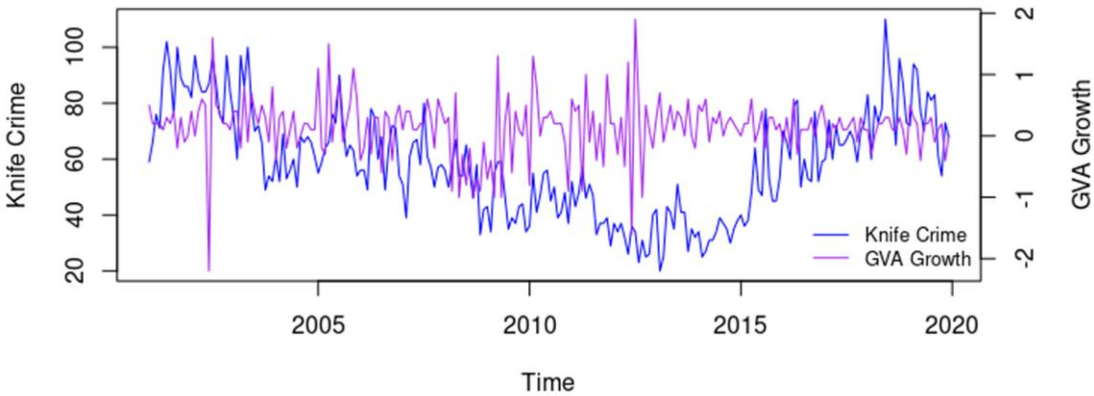


Figure 16: GVA growth and knife crime

Again, Granger causality testing shows that GVA growth does not Granger cause knife crime[5].

Another way to examine the potential relationship between these variables and their relationship to knife crime is jointly through a directed acyclic graph (DAG). This is essentially a causal model that can include the input of SMEs (in terms of the direction of links), can be estimated, or both. In this instance, as there is no clear evidence that there should be a link between these variables and knife crime, or if there is what the direction is, the DAGs presented here have been estimated only[6].

As can be seen from the chart below, when a single DAG is estimated there is a link between inflation and knife crime; however the link between knife crime and unemployment is likely in the wrong direction. There is also no links from GVA growth to any of the other variables.

However, when the data are re-sampled and an average of many DAGs is taken[7], whilst there are still no links between GVA and any of the other variables, both the unemployment rate and inflation directionally link to knife crime.

[4] BIC difference ratio of -0.8 .

[5] BIC difference ratio of -1.13 .

[6] Using a hill climbing algorithm.

[7] The data were bootstrapped 1,000 times and the average of the resulting DAGs is taken.

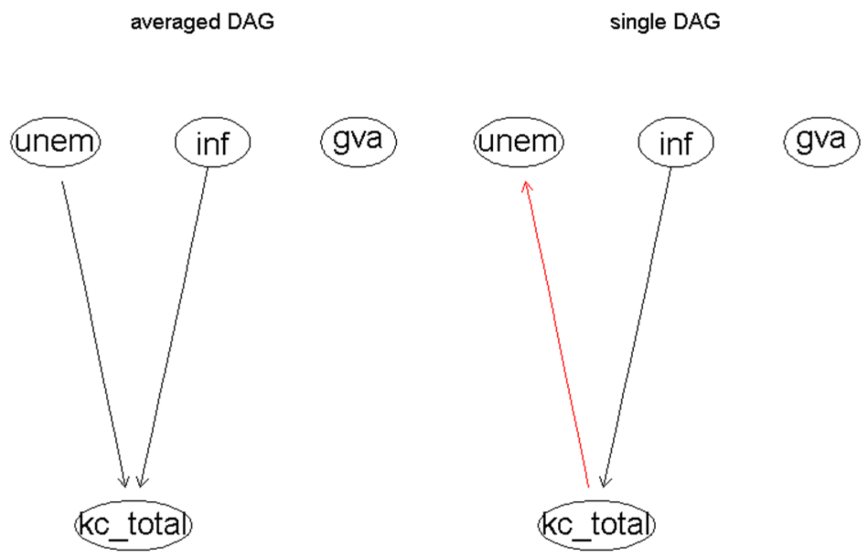


Figure 17: DAG of unemployment, inflation and GVA with knife crime

The lack of a connection from GVA growth to the other variables is most likely due to the sudden and extraordinary drop in GVA seen in 2020. Purely to see if there is a potential relationship between GVA growth and the other variables (including knife crime), the large drops seen in 2020 were replaced with the previous 5 months' mean growth rate. Taking this approach leads to:

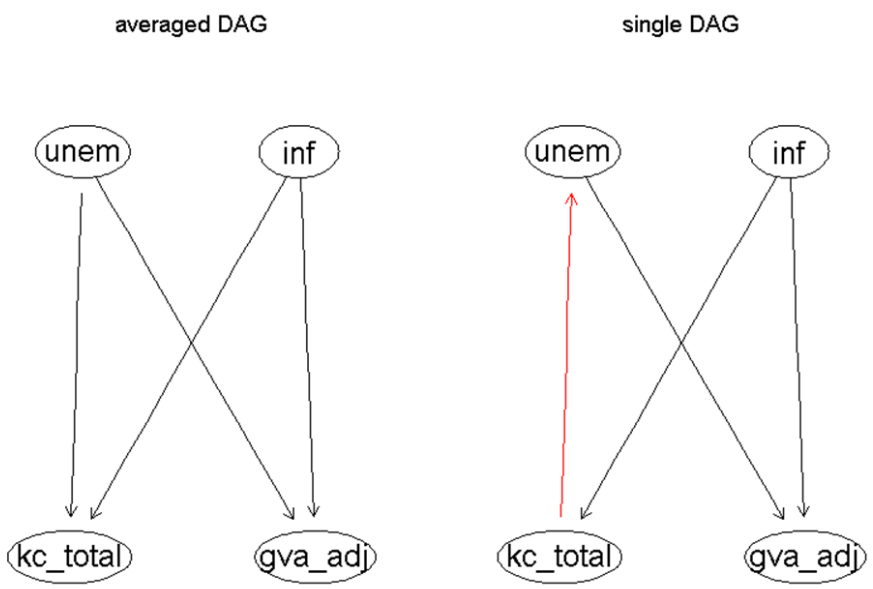


Figure 18: DAGs resulting from adjusting GVA growth

The previous links remain, with the averaged DAG showing directional links from unemployment and inflation to knife crime. Whilst GVA growth does not directly link to knife crime, there are estimated relationships between unemployment, inflation and GVA growth. Particularly the direction of the link between unemployment and GVA growth is perhaps in the wrong direction logically, in reality this is likely to be a bi-directional relationship (so a cycle type relationship may actually be the case).

This analysis provides some evidence of links between wider socio-economic variables and knife crime.

The literature, taken as a whole, indicates that there may be a negative relationship Police numbers and knife crime. We have been able to receive annual data regarding the total numbers working at WMP (staff and officers[8]), this does seem to show a negative relationship:

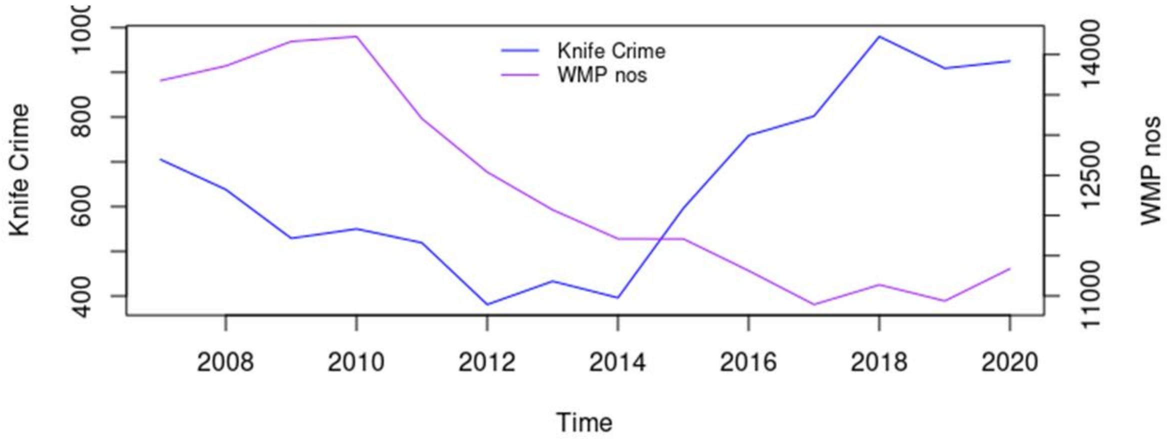


Figure 19: WMP employment and knife crime (annual figures)

Interestingly, this does show Granger causality (so indicating a relationship between numbers employed by WMP and knife crime)[9]. Because of the annualised data (and so smoothing of the data as well as a low number of observations, this should be taken as weak evidence of a (causal) relationship between the two.

[8] Police staff are included as the functionality of the Police would be hampered without them.

[9] BIC difference ratio of 0.36; the BIC difference ratio

5 A Lower Spatial Level

As noted above, there is considerable variation present in the number of knife crimes at the local authority level with Birmingham having the largest number (and lowest amount of variation).

Across the different local authorities there does not appear to be much spatial autocorrelation:

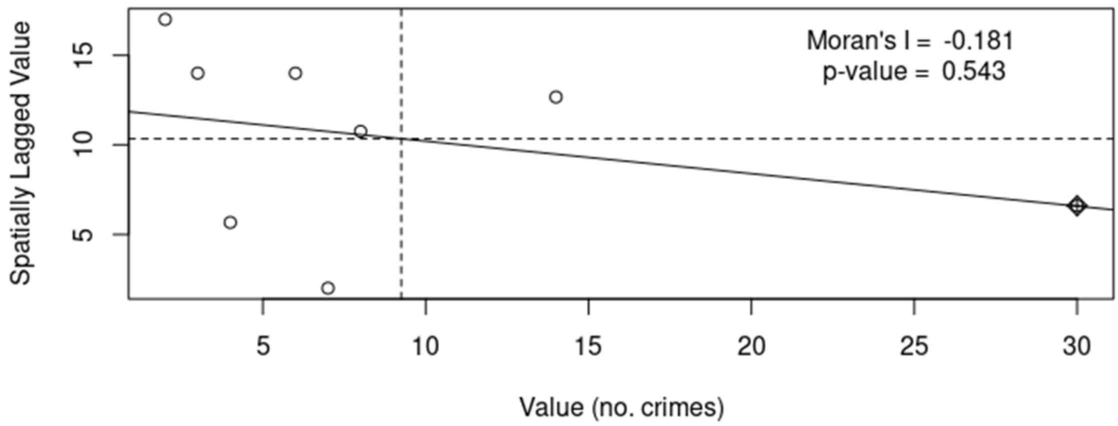


Figure 20: Spatial autocorrelation in knife crime between local authorities

This lack of autocorrelation is likely due to the large spatial scale of this analysis.

It also means that a spatio-temporal model is not as effective as a time series model for forecasting:

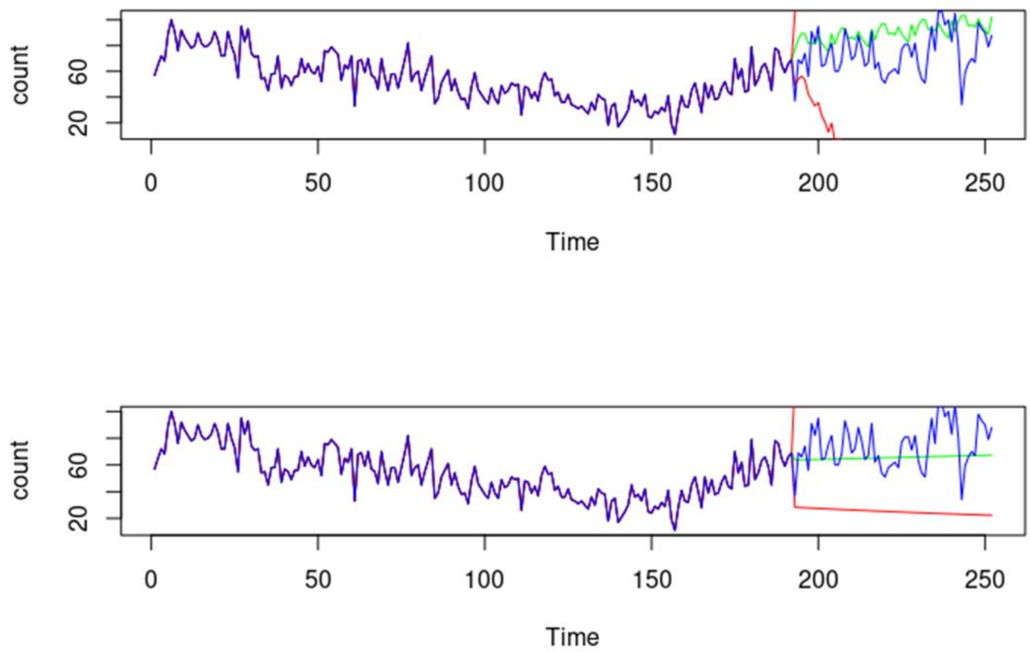


Figure 21: Comparing time series forecast (top) to spatio-temporal (bottom)

Spatio-temporal models were tried with forecasting both Coventry and Dudley and they performed poorly compared to a time series model.

This apparent lack of spatial autocorrelation is perhaps slightly surprising given that there is (essentially looking over time), some degree of (Spearman) correlation between the different areas' levels of knife crime, perhaps particularly between Birmingham and the other areas:

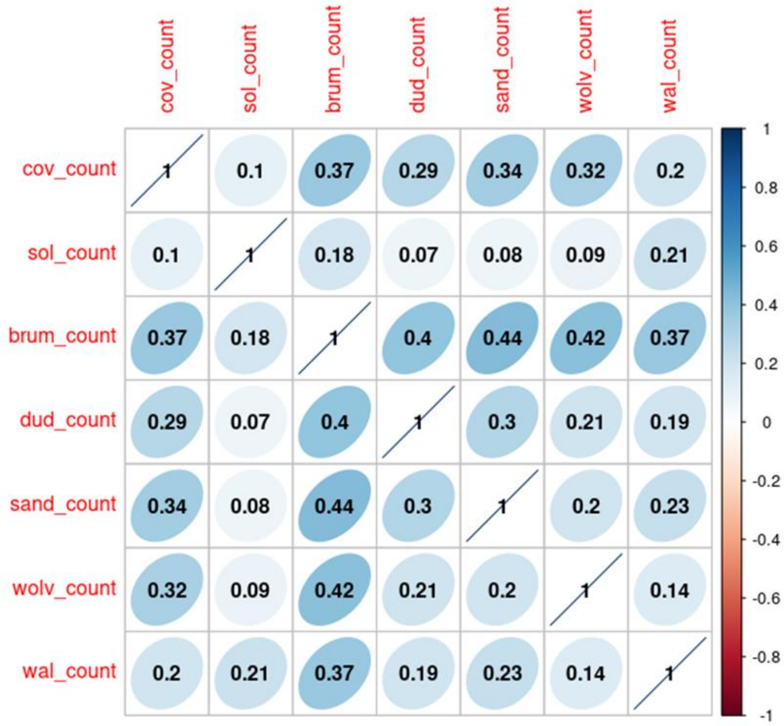


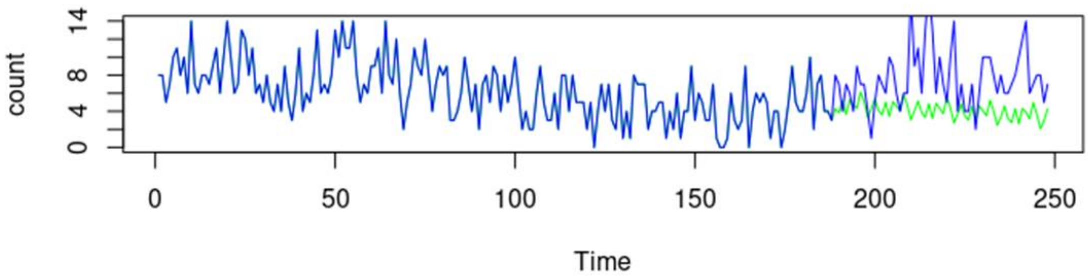
Figure 22: correlation between different local authority areas' knife crime

As an alternative, use has been made of the proportions that each local authority areas' levels of knife crime contributed to the total seen in the whole WMP area.

This has been looked at both forecasting the proportions using a time series approach and simply applying the average proportion to the forecast of total knife crime over the whole area (the proportionate number of knife crimes seen in each of the local authority areas tends to have a constant mean level with variation as opposed to the count which tends to have similar changes in the trend as has been seen in the total number of knife crimes).

Forecasting the proportions and applying these to the total forecasts produces a higher prediction error than simply applying the mean proportion to the total forecasts[10]:

[10] Applying the mean proportion with the mean estimated over the previous 1 – 5 years was also used, but each of these mean proportions led to higher prediction errors than using the mean calculated over the whole period.



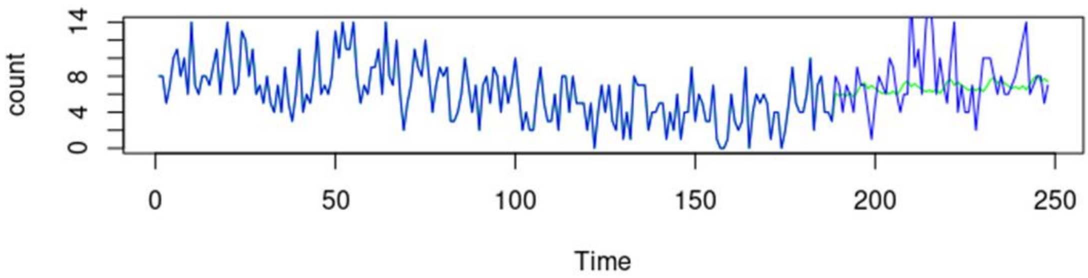


Figure 23: Forecasting proportions and applying to total area forecasts (top) and using mean proportion applied to forecasts for total WMP area

Model Approach	RMSE	MAE
Time series of count	4.5487	3.3306
Time series of proportion applied to count	4.9423	3.754
Mean proportion applied to count	3.4115	2.3725

6 Conclusions

Given that monthly data are used, asking models to forecast 60 time periods into the future is asking a quite a lot. However, two of the basic modelling approaches used seem not unreasonable in performance.

Whilst there is some (weak) evidence of a relationship between knife crime, socio-economic and infrastructural variables (namely the claimant count unemployment rate, inflation, (adjusted) GVA growth and knife crime (used causing injury), any relationship appears weak with the data available.

Furthermore, to be used for forecasting, these variables would themselves need to be forecasted and it is highly likely that any such forecasts would introduce large increases in uncertainty with likely minimal improvements in accuracy.

As such it would appear that a more simple approach is beneficial which, taking realistic forecasts into account, is the Bayesian state space model:

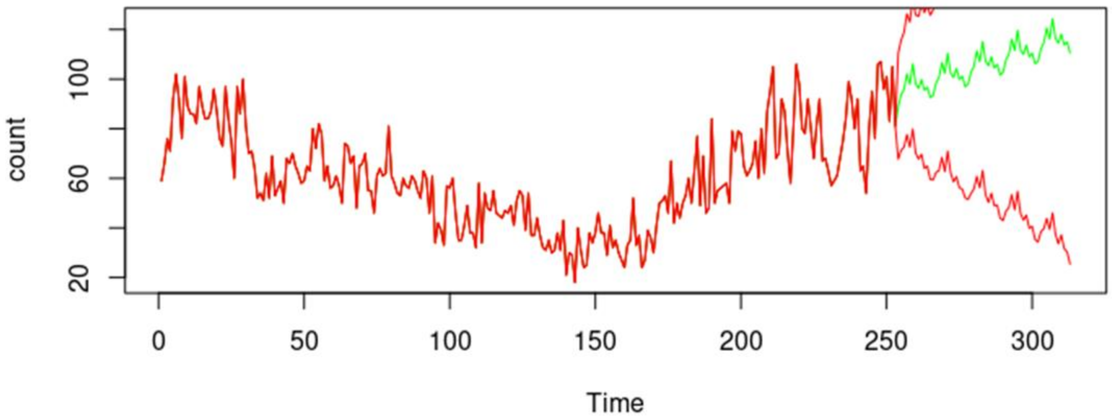


Figure 24: Forecasts of knife crime (used causing injury) from February 2022 - January 2027

It is possible therefore that in the absence of effective preventative measures, monthly knife crime (used causing injury) could continue to increase.

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