Predicting the Volume of Demand from Mental Health Related Police Incidents

Data Analytics Lab

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Introduction & Summary

Mental health is becoming an increasingly important part of frontline policing in the community. It is believed that between 20% and 40% of police time is spent dealing with mental health related calls and incidents. HMICFRS (2018) have previously expressed concerns that the police are working beyond their remit and that there is not a clear picture of what is *actually* faced on the ground. The triage groups are able to assist, however this is currently dealing with only some of the demand. These triage teams were piloted in 2014 and aim to attend incidents where there is a mental health dimension in order to reduce demand by giving individuals advice on the best services to use or access.

The most prominent events such as those people who end up being sectioned under the Mental Health Act are not a large number of the overall data. A lot more lower level mental health issues are dealt with in day to day policing. Little is understood about this. The lack of understanding of mental health in general will likely become increasingly important as the COVID-19 pandemic develops and the public as a whole become more stressed and pressured by the requirements to keep the spread under control (for a discussion of this see amongst others Rogers et al. 2020).

This report is made up of a number of elements. The first is a descriptor of the data currently available in the West Midlands systems. This has two purposes; firstly to assess the actual data and to be aware of the short-comings and ongoing data changes, which are substantial. The second and more technical element is to develop a predictive model as to the number of MH incidents that could be faced by WMP so as to develop a picture of likely demand (and to assess the relationship, if any, between certain factors and MH incidents).

Important Findings & Variables

- There is considerable *new data* available to WMP and this should be considered once there is *sufficient* to use effectively
- Approximately a third of mental health incidents are not flagged as such directly
- Wards with *high levels of demand tend to remain high*
- Predictions suggest a number of wards with higher demand
- The number of *Mental Health Service Providers* in a ward is an important factor
- Levels of *Violent Crime* & Theft are important variables and to a lesser extent, drugs and harassment incidents and crimes generally
- The number of Mental Health Act classifications at a number of *Custody Recording stations*
- There is *clustering* in certain wards with a neighbourhood impact
- A combination of a *spatially informed* model and a simple *time series* model predict aspects of mental health demand
- Information from Partners will likely aid understanding
- We are living in *extraordinary* times currently and the relationships might not remain stable

The models are described and discussed in the report, with the more technical aspects in a technical appendix. The models are based on *wards* and a *monthly* forecasting window. They produce a baseline of what might be considered normal and then project one month ahead. Wards are used rather than policing areas or neighbourhoods due to the requirements to report to local partners who work in wards. Maps of the predictions are presented in the report and can be seen to show a number of areas or corridors where there is predicted to be higher levels of incident or crime of the characteristics considered here. It is in these areas that the triage crews might wish to focus or be located so as to ensure that those with mental health issues can have the best possible consideration by those in WMP.

WMP has piloted and recently rolled out a new system for recording information associated with incidents involving Sections 135 and 136 of the Mental Health Act. The data is associated with Place of Safety Monitoring. The new data coming online has some useful information which will aid the Force's interaction with those dealing with mental health issues. If this can be accompanied by external partner data, then it will become possible to build a richer picture of the demand for policing that has a mental health aspect and to aid the WMP to assist the public in the most efficient manner. It should be noted that no partner data are currently available.

There is scope for developing further understanding of the mental health related demands on WMP and as demonstrated here, the geographical impacts are important. This will be reflected potentially in partner data, be it health care information or other services that can provide data on mental health service provision in a particular ward. The results suggest that this might add value to the data and allow more effective provision of policing services to those with mental health needs.

For all acronyms please see the Glossary at the end of the report.

Scope of Project

This project is the start of an on-going consideration of the information and use of information concerning mental illness and mental health associated demand. The data available in WMP is the main focus of this project, of which this report is a part. There are two elements of this work. Initially the baseline or 'norms' in the level of mental health associated demand and the predictive element. The aim is to give an indication of where there is likely to be significant demand. Currently this work is descriptive and predictive. The focus is on the numbers, actual and predicted in particular areas.

The changes in the data structure[i] in WMP and the COVID outbreak has meant that the data is currently less than ideal. With this in mind, some modification of the modelling is foreseen at a future date to improve the consistency of the modelling using only ControlWorks data rather than combining OASIS with ControlWorks and then the other systems. Certain aspects of the incidents and crimes are investigated especially drugs incidents and crimes related to mental health issues.

It should be noted that the area of interest is the ward not the neighbourhood or other policing region. This was by request and will lead to somewhat different aggregations than are usual. This request was made as the reporting across partner agencies is by ward and thus it is sensible to meet these requirements directly, rather than face disaggregation at a later date. Likewise the data is aggregated monthly to meet reporting requirements. This will be the time unit for the analyses.

Since July 2020, data has become available via a new Section 135/136 form developed by officers associated with mental health assistance and triage. This is still in its infancy and there will be an opportunity to build on this information once there is more of it available. This promises a more detailed understanding of the interaction between WMP and those with mental health problems.

ICIS (the custody system) is an obvious source of information, though there is a high level of potential issues with those arrested potentially being not completely transparent with their mental health situation. The usual searches and flags were used to extract the data of interest. The report shows that the custody suites deal with the majority of the cases and there is a great deal of variation associated with these detainees. Those with a flag corresponding to the Mental Health Act were used in the analysis as well as the count of those per month sectioned across the WMP area. Additional information was gleaned but this was not included in the baseline model. This included circumstances under which the detainee was brought to the station and offence summaries.

The COMPACT data (the system for recording details of missing persons) is also available for use; unfortunately the data is missing locational data in many cases and is of limited use in its current state except as a barometer variable where the number of missing persons is a flag for the current and future demands.

The main source of information therefore are the Crimes and ControlWorks databases. The data is considered for the models over nearly two years. The data was not taken back further than January 2019 as the change in systems meant that the two data sets were not completely comparable and the forward facing nature of this work means that the emphasis should be given to the development of the ControlWorks data.

The data also includes the presence of mental health service providers in the ward as this is an important element of dealing with the increased likelihood of incidents with a mental illness dimension. Currently repeat persons are not dealt with explicitly. These will more likely be best dealt with using the additional information which is more in depth than the current systems.

The models are presented in the Appendices along with a number of diagnostic tests. The summary of the models is given briefly along with one set of results for the determinants of the demand in the region as an example of the information presented later. The modelling has been made more complex by the current pandemic. This was considered using a simple shift parameter and this is clearly a matter for on-going consideration and will be returned to as the modelling is extended and implemented in an operational framework.

There is currently relatively little literature in the area under consideration; most mental health literature looks at the role of mental illness in the prison population rather than at large in the community and its effect on the provision of policing. There is a discussion of this in the report in the relevant sections.

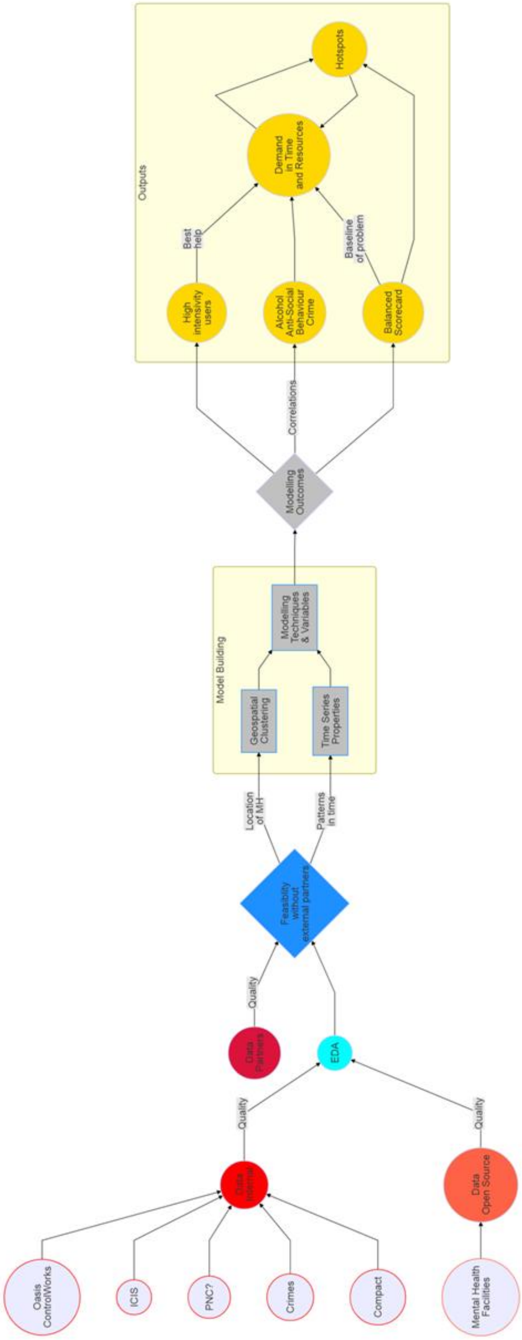


Figure 1 Data Approach to Mental Health

Data Description & Exploratory Data Analysis

This section considers the data in the West Midlands Police systems in addition to a single publicly available open source data set based on the providers of mental health services. This is the foundation of the initial modelling. For all acronyms please see the Glossary at the end of the report.

ControlWorks & OASIS Systems

As might be expected, the policing service has significant contact with those suffering from mental health episodes. Despite this, the data flagging mental health related incidents is of variable quality. ControlWorks has seen an improvement relative to the Oasis system, though there is still a need to use searches of the free text to find incidents associated with mental health related incidents. Approximately 81% of the data are incidents and 19% ROCs (Record of Contact).

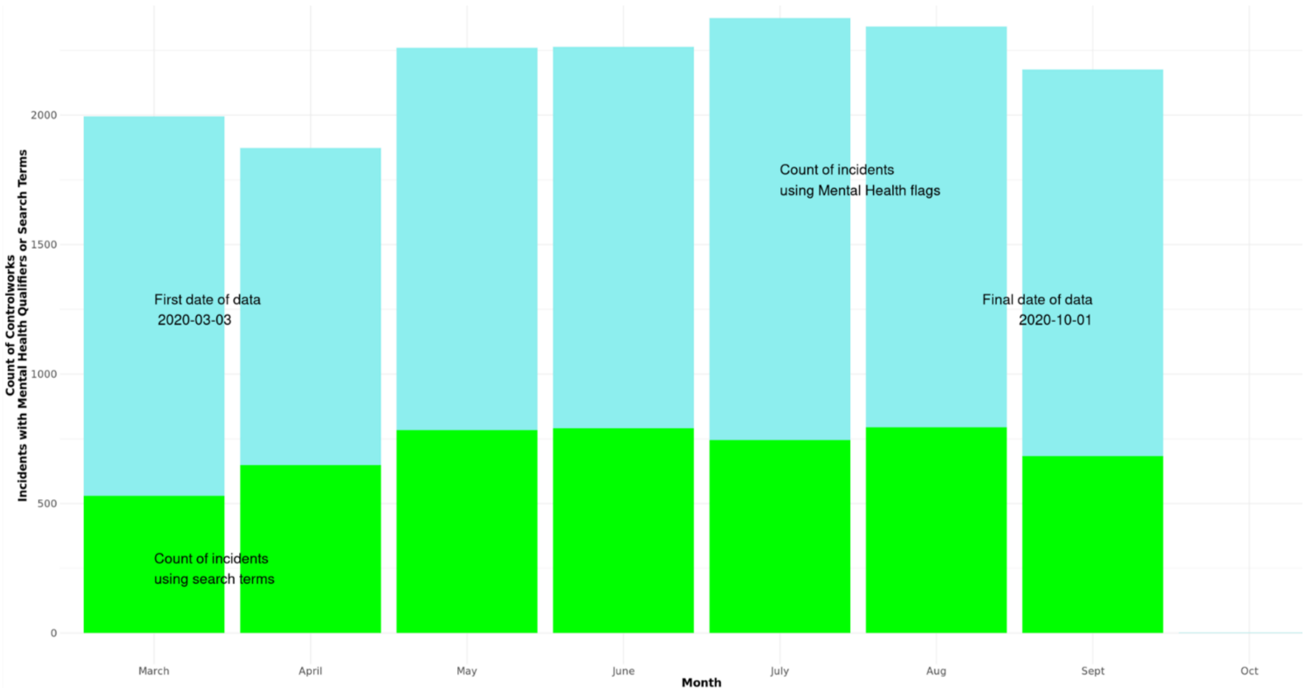


Figure 2 ControlWorks Incidents Associated with Mental Health

The flag is included in a majority of the cases in ControlWorks, though there are still a significant proportion of incidents where the search terms were used to identify the incident. Excluding October, the mean proportion is 32.5% of the cases highlighted.

Table 1 ControlWorks Data by Flag Usage

Criterion	March	April	May	June	July	August	September	October
Mental Health Flag	1465	1225	1476	1474	1629	1546	1491	2
Search Criterion	530	648	784	790	745	795	684	1
Proportion Using Search Terms (%)	26.57	34.6	34.69	34.89	31.38	33.96	31.45	33.33

The search terms were based on those used by current Subject Matter Experts (SMEs)[ii],

The incidents are primarily concentrated in the population centres as can be seen in Figure 3. The map further shows the ward boundaries in the area under consideration. The data has been focused on to the West Midlands. The urban focus is as expected.

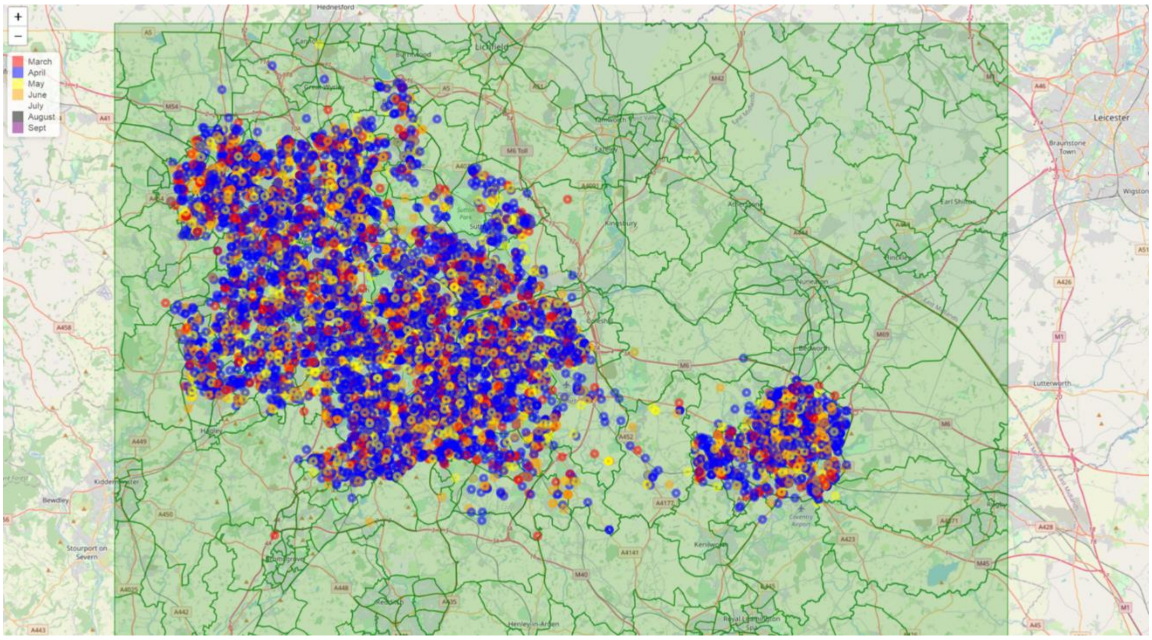


Figure 3 Map of ControlWorks Mental Health Incidents

The OASIS data uses a similar approach to the ControlWorks data. A combination of search terms and flags are used to highlight the relevant incidents. It should be noted that the last three months of the OASIS data and the first three months of ControlWorks are a little different than previous years as there has been a shift into lockdown due to the COVID-19 pandemic.

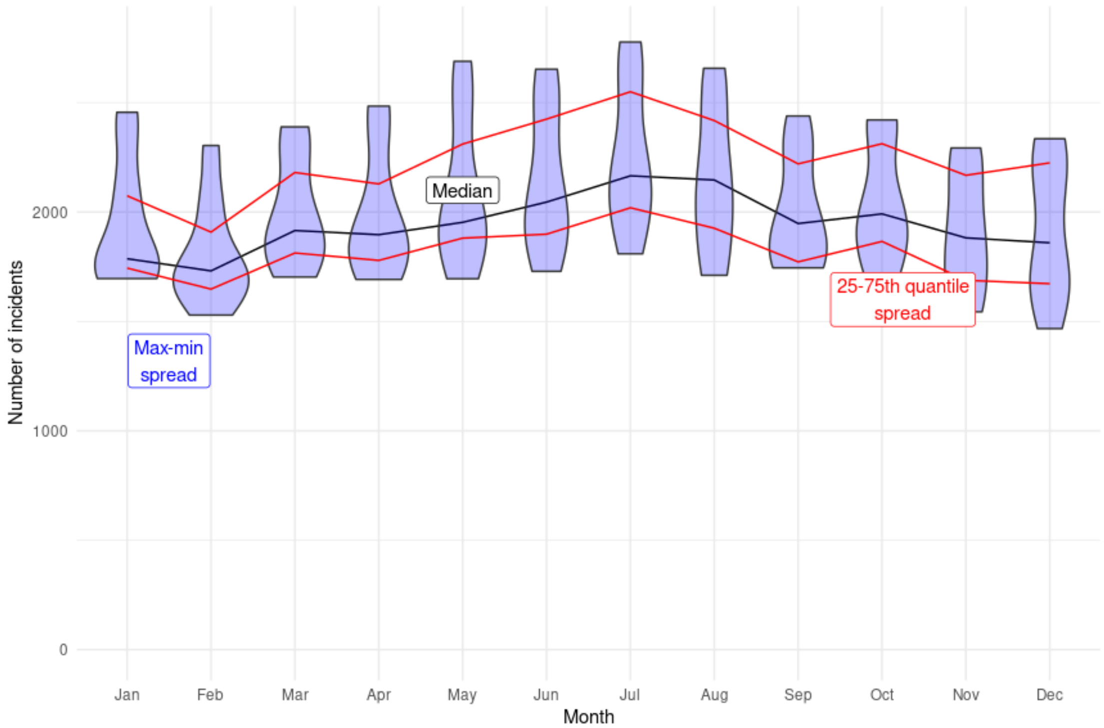


Figure 4 Median Monthly Counts of Mental Health Related Incidents in Oasis

From figures 4 and 5, we can see that the number of incidents related to mental illness tend to increase during the summer months and from Figure 5 it is possible to see that there is a slight upward trend in the data in the period 2010- 2019 in the Oasis data. The final year was dropped as can be seen only two of the final three months could be used.

These data suggest that there is a degree of continuity in numbers of the mental health related incidents between Oasis and ControlWorks.

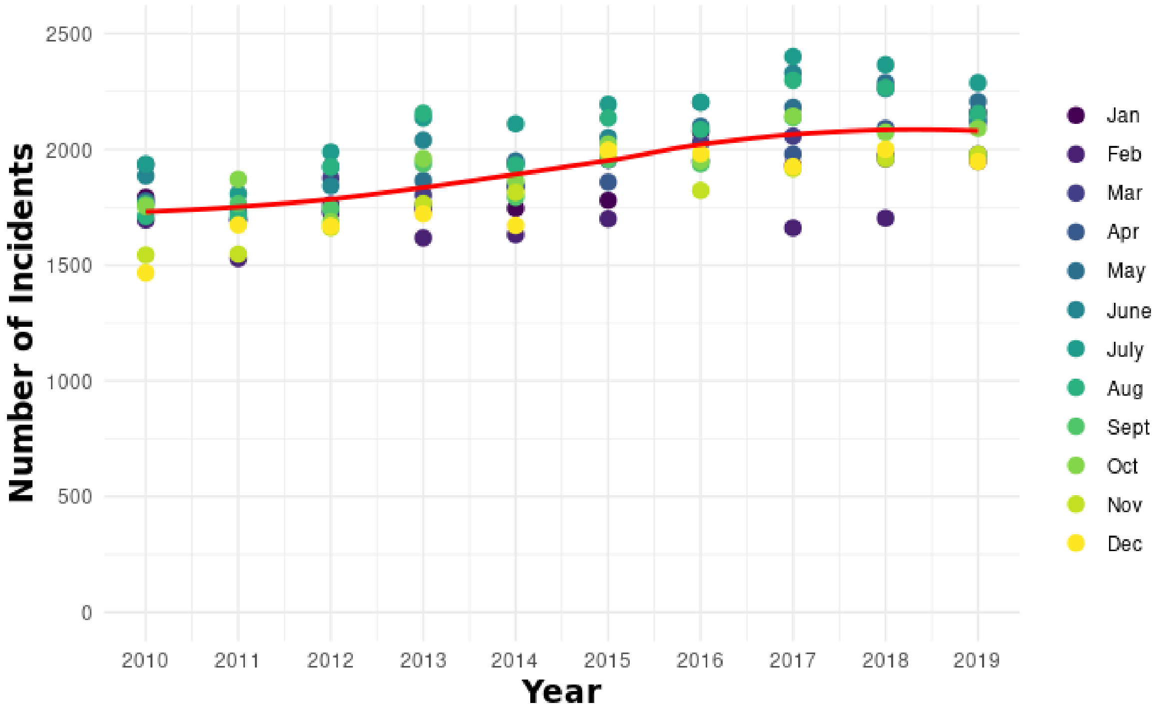


Figure 5 Oasis Data By Month & Year

As with the ControlWorks data, approximately one third of the incidents where a mental health aspect was involved required textual searches rather than the flag to identify those incidents. It is also noticeable that this proportion has increased over time as shown in Figure 6. In other words, fewer incidents are logged with the relevant data flags in the underlying data. The reason for this is not clear; apocryphally there were changes to reporting so that it used to be the case that the reports changed away from a check box report for mental health.

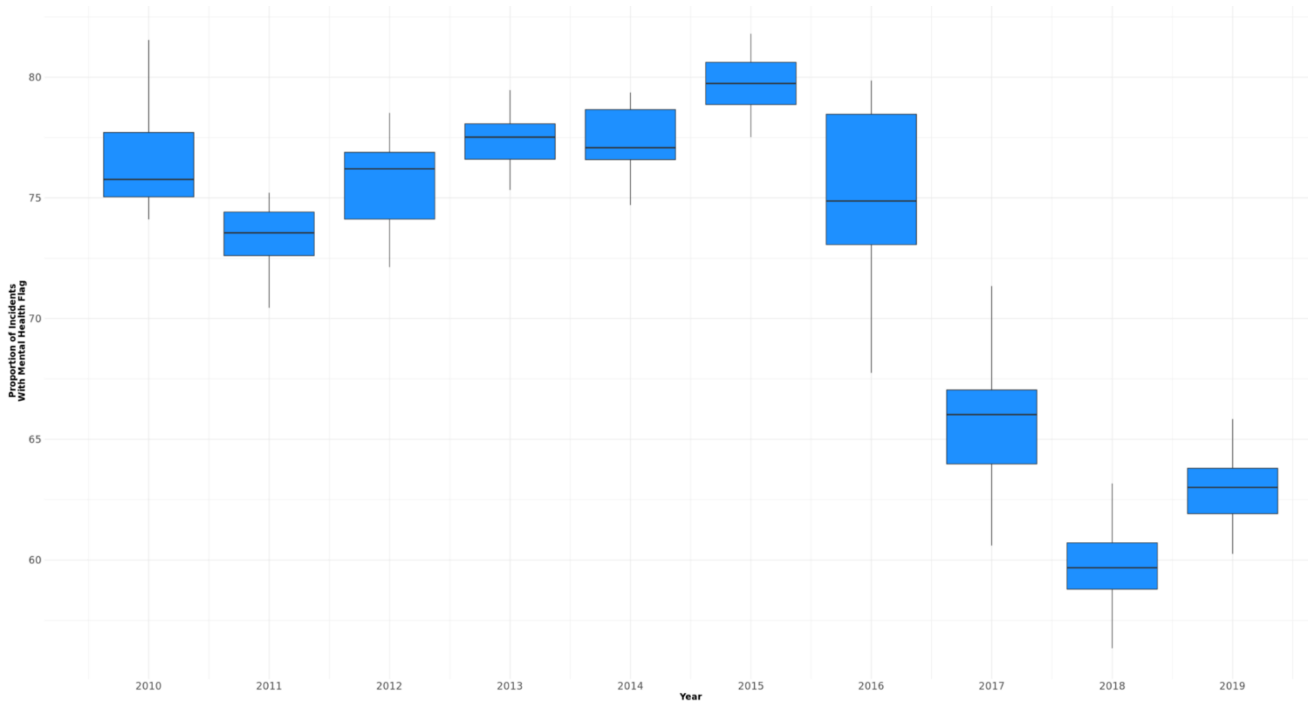


Figure 6 Proportion of Cases Using Flagged Fields in Oasis

The underlying incident numbers are generally consistent across systems however there are further issues with the classifications associated with these two systems. The classifications used are those in ControlWorks to ensure that the models can be forward-focused.

This data demonstrates that there is a great deal of information in the ControlWorks and OASIS systems; unfortunately about one in three cases do not fully take advantage of the systems capabilities which means that the data available to the WMP is more limited and less robust than we might wish.

COMPACT System

The COMPACT database contains information about missing persons. As would be expected there is a significant number of mental health issues associated with missing persons as has been described by Greene & Hayden (2014) and Sowerby & Thomas (2017). Indeed the All Party Parliamentary group (2018), suggest that the number might be as high as 80% of those who go missing have some mental health issues. Ann Coffey (op cit.) explicitly states that this is not a police problem, though they are alone in dealing with the issue. This appears to be some of the experience of WMP.

The data about mental health is spread around the COMPACT data. There is only limited date information that can be consistently relied upon. There is a mine of information in COMPACT but it appears to be mostly unconnected (in that there are no immediately obvious links between the various elements) and not used in a consistent manner as it is an older system designed for recording & retrieving information about cases rather than a more macro- analysis.

The Compact data unfortunately includes only three entries:

- Dementia
- Depression (including suicide)
- Other

These are rather wide classifications and so they are used in conjunction with additional information within Compact which includes considerably more data in the notes field. However, the data necessitates searching the data for key words and phrases. These include *Depress*, *Schiz*, *Psycho(t or s)* amongst others, including any discovered spelling mistakes. The terms are more illness related than other systems as the missing person can be described as suffering from a particular illness or being on (or not having with them / missing) specific medicines.

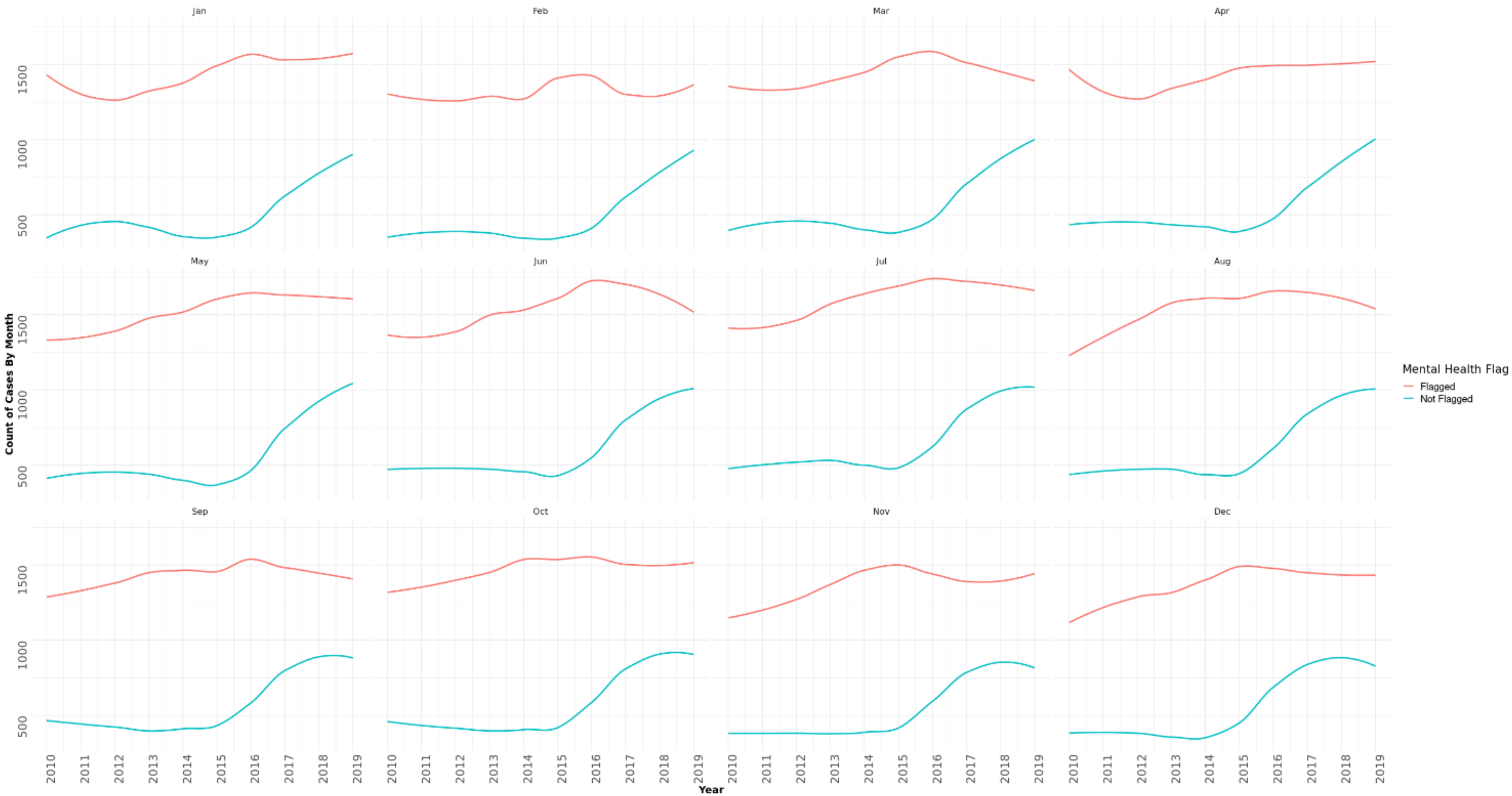


Figure 7Monthly Trends in Using Mental Health Flags

The combined data in the compact database is missing locational data for the relevant records. It is possible to date the missing person's disappearance, using an earliest date from the record (excluding dates of birth). There is however an anomalous period on 7th December 2015 where a vast number of records were modified or added. This can be seen in the various time series and data graphs in Figure 8. The second graph has removed the data from December 2015 to see a more *usual* situation. Where there are no other date data, this has been used, but it should be noted that this is likely to be a construct of the database rather than actual data regarding incidences. The time series aspects of the data are described below. The data includes multiple instances of an individual being reported missing as an individual who goes missing is a new call on resources irrespective of whether this is persistent behaviour or not.

From this it is possible to see a slight seasonality, with reductions in the winter months but these are inside the error margin. Given the limited nature of the data and its quality, this level data might be helpful in a model as an environmental variable, picking up bad months or worse months. For children, both boys and girls tend to go missing in approximately similar numbers; whereas in the case of adults, men have slightly higher numbers going missing. The generally low numbers, especially with respect to children appear to be due to the lack of relevant phrases in text fields.

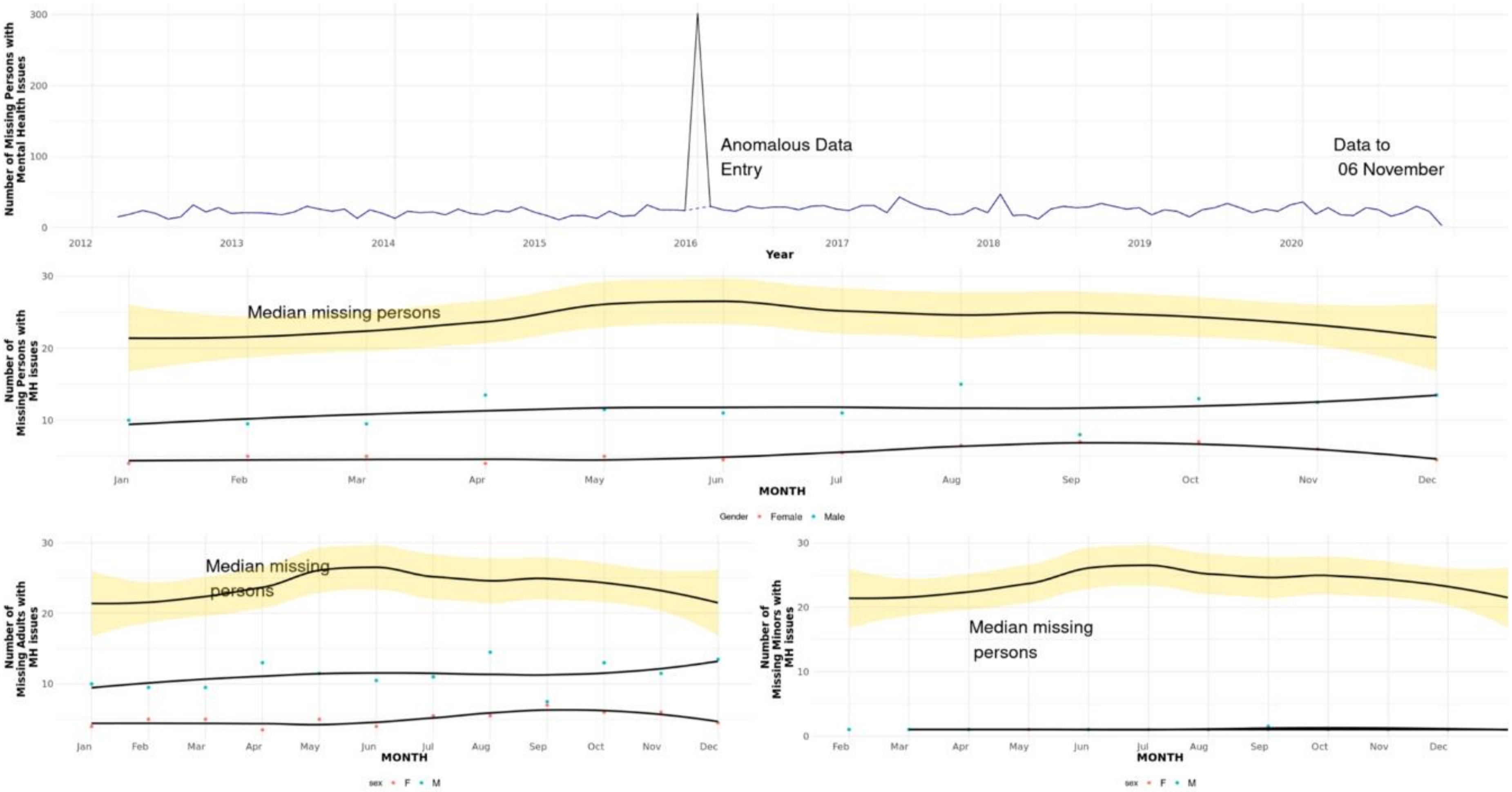


Figure 8 COMPACT Data Split By Year & Month

CRIMES System

Rather than going via the incidents as recorded in OASIS or ControlWorks, it is of course possible to look at Crimes directly. The Crimes Data field codes of VU8 (mental vulnerability) and YP1 (self-harm) and text searches in the relevant fields are used to extract the information. Initially only defendants and suspects are considered. To include suspects is important as these people are directly interacting with WMP and in order to deal with them sympathetically it is important to understand that they will be part of the demand directly.

We can consider the crimes flagged in the data directly or in a search of free text fields. The small number of those incidents with a sex labelled unknown or NA were removed as there were very few data points (removing this is only for diagrammatic purposes. This data is included as is in the analysis). In order to ensure a consistent mapping with earlier graphs, 2020 was removed for the monthly analysis. The annual number of cases involving mental health issues have seen an increase (though the method of flagging these has become only textual in the relevant notes field). Figure 8 shows the growth in these numbers are parallel between genders, though there is evidence in the population as a whole that women are more likely to be *diagnosed* with mental health issues (for example WHO 2001).

Figure 9 Crimes Numbers by Gender & Time

Unfortunately the CRC codes cease to be used in 2012. This therefore requires the use of text processing to ascertain those crimes where there are mental health issues.

Rather than approach the crimes directly, it seems therefore beneficial to follow the incidents from Oasis and ControlWorks though the Crimes dataset. The data used in the modelling is based on this.

The models considered use incidents only, such that those involved have some problem with their mental health to such a degree that this is mentioned, and the Defendants and Suspects when the model deals with Crimes with some association with mental health. A further avenue of work would be to look at the role of mental health as a characteristic of *victims* rather than perpetrators.

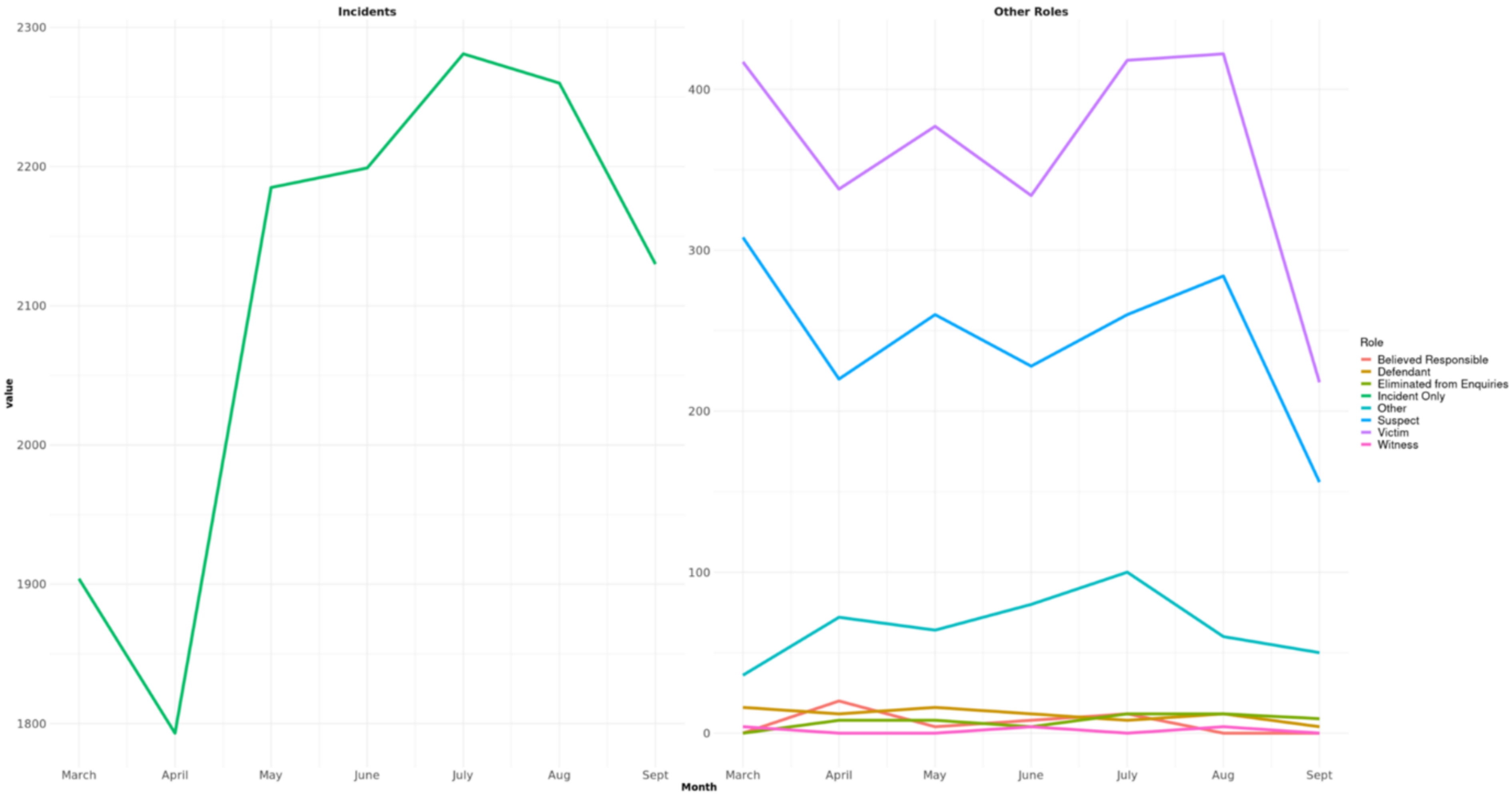


Figure 10 Linked Crimes and ControlWorks Incidents with Mental Health Associations (March- September 2020)

ICIS System

Further along the path into the criminal justice system, the custody records are also a record of the police's interaction with those suffering from mental illnesses. As with other data sources, the text was mined for signs that the person in custody has a mental illness or problems with their mental health. The language was found to be more formal than elsewhere in the data which aided in the search. There were a number of false positives discovered (especially Audi S3 leading to problems). The data was filtered on date, person identifiers and custody record numbers. This removed most of the duplicates, though it is still possible that someone was arrested twice on the same day with a different custody number.

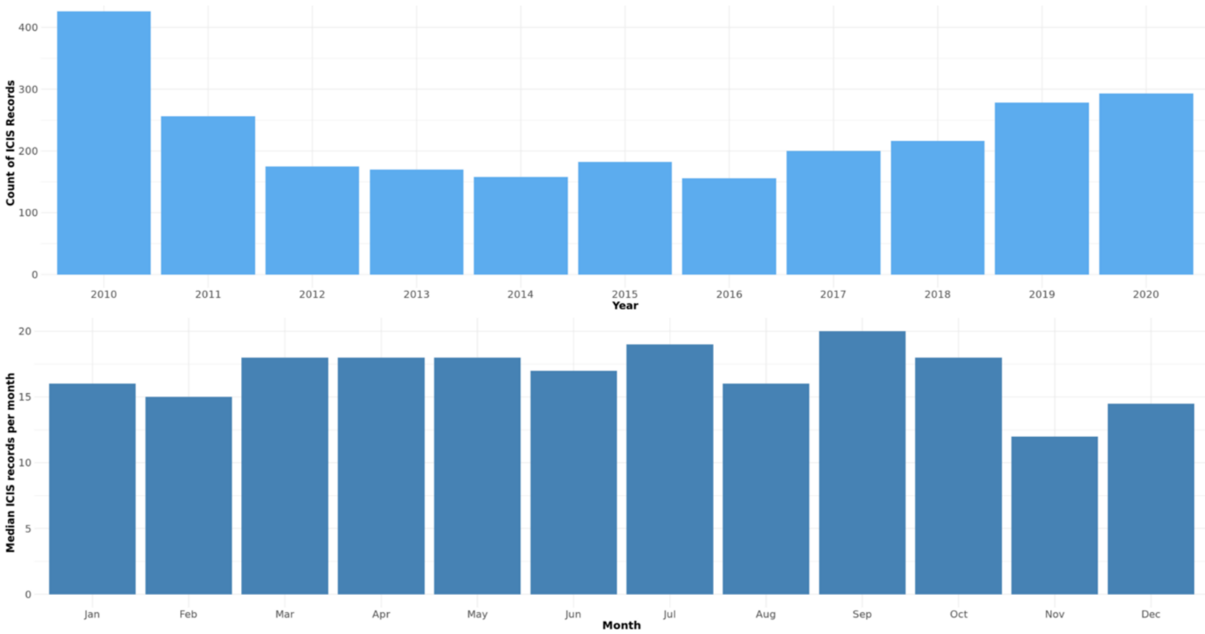


Figure 11 ICIS Records with Mental Health Associations

From the data we can see that there has been some variation over the past decade, with a decline in the early 2010s. This is believed to be a data issue rather than a change in the underlying mental health of those in custody.

The data was split by ages and locations. The locations were considered to be a requirement as this parallels the provision of mental health services in the various wards.

Those in their mid to late 20s and into their thirties are the most populous group suffering from mental health issues, though the younger detainees are seeing a growth in the proportions in custody. This is shown in Figure 12.

As can be seen inFigure 12, there is clustering in Custody stations (referred to as recording stations in the database) which is quite stable through time. A number of these are used in the modelling of the base line as they reflect the general WMP area's situation in a broader manner than the direct ward variable due to the fact that officers bring detainees to more central regional points and this further reflects the population centres in the West Midlands and policy decisions by WMP in locating the custody centres (which started in 2016 before this study).

Figure 12 Age Groups Associated with Mental Health Problems in Custody

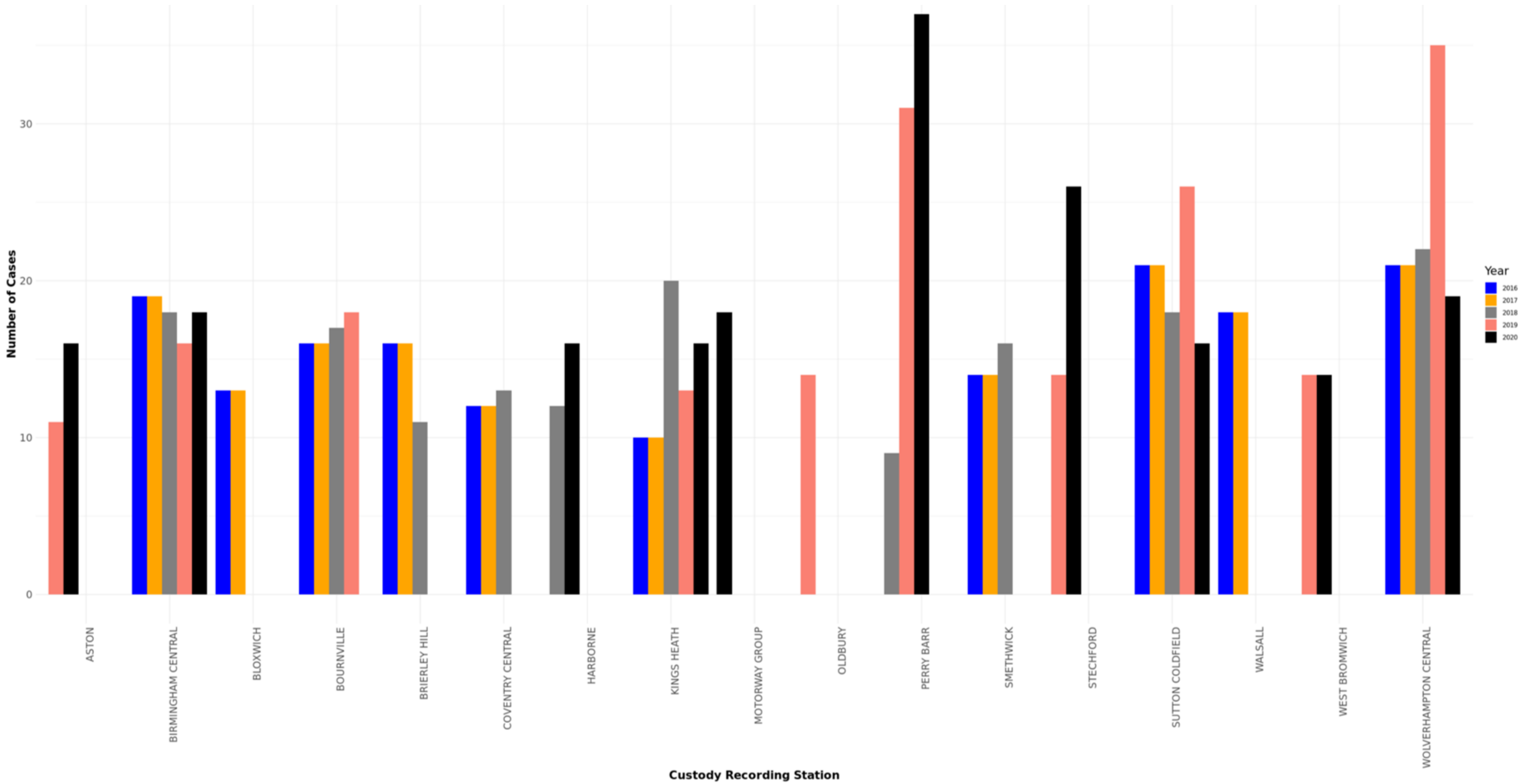


Figure 13 Counts of Mental Health Custody Records By Custody Recording Stations

Mental Health Providers

A spreadsheet was provided by a local subject matter expert with the main mental healthcare providers. This is a varied list ranging from psychiatric institutions to dentists. There are nearly 180 different providers of different sorts in the region. These are used as another measure of the ward's provision of mental health services in general. It is hypothesised that the number of incidents in particular will be positively related to the number of providers in the area, either because incidents happen at the provider or because the incidents involve patients living nearby. Data suggests that the place of health care and the nominal's home addresses or incidents[iii] are generally close to each other.

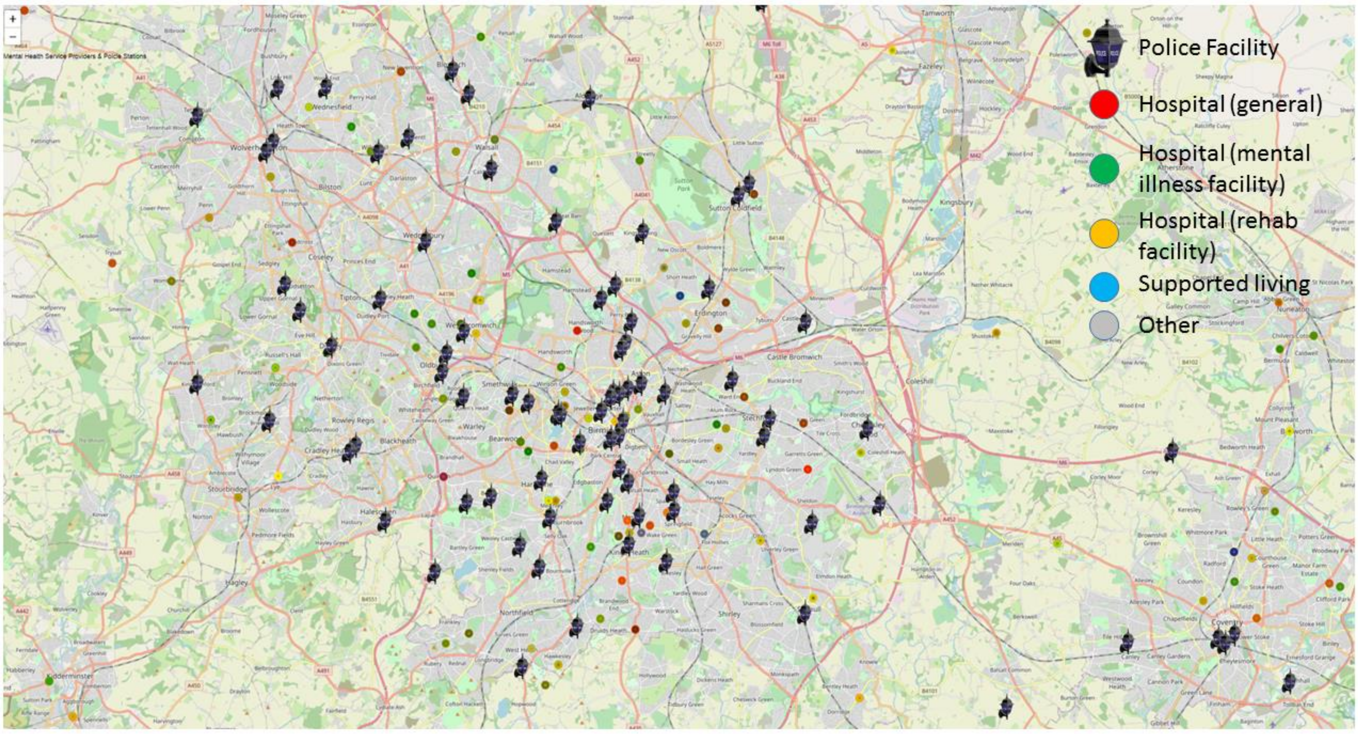


Figure 14 Map of Mental Health Services in the West Midlands

The distance between incidents and the providers is low- the median is just over 1km and the mean 1.25km. Solihull, Coventry and Wolverhampton have higher mean distances, though the median distance for Coventry is lower than the mean distance. As would be expected, the distances for the Birmingham incidents is lower than those in the other areas.

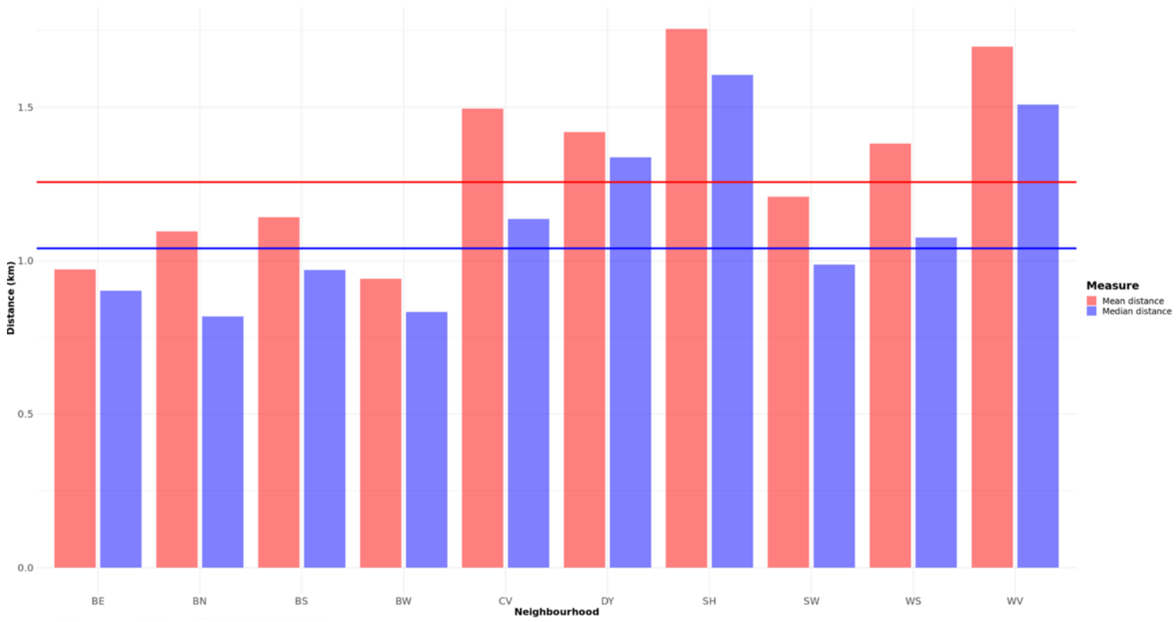


Figure 15 Distances between Incidents and Healthcare Providers

This data suggests that locality is an important factor in the incidents and healthcare provision. Incidents are often less than a mile away from a mental healthcare provider of some sort. This also implies that if a ward has a large number of providers it might experience higher levels of mental health incidents. Note that these providers are not of any particular service, but any mental health care service provision. One might argue, legitimately, that some of these providers are *accidental* providers of services and it is not their core purpose. This would increase the mean and median distances; this is true but the providers are acting as a proxy for understanding about mental healthcare in the community in that ward.

Solihull & Section 136 Place of Safety forms

WMP has previously trialled a set of forms to help triage incidents with mental health connections initially in Solihull. This has been rolled out to the rest of the WMP area and until the end of September the data gives around 600 records, though some of these are obviously test cases. This data has considerably greater granular information that will be of use in considering the role of mental health in the future, but currently the data does not link sufficiently well in to the main systems. It should be looked to be continued and linked more robustly into the main systems.

The data gives information concerning the age groups and the sections of the Mental Health Act under which the person was detained.

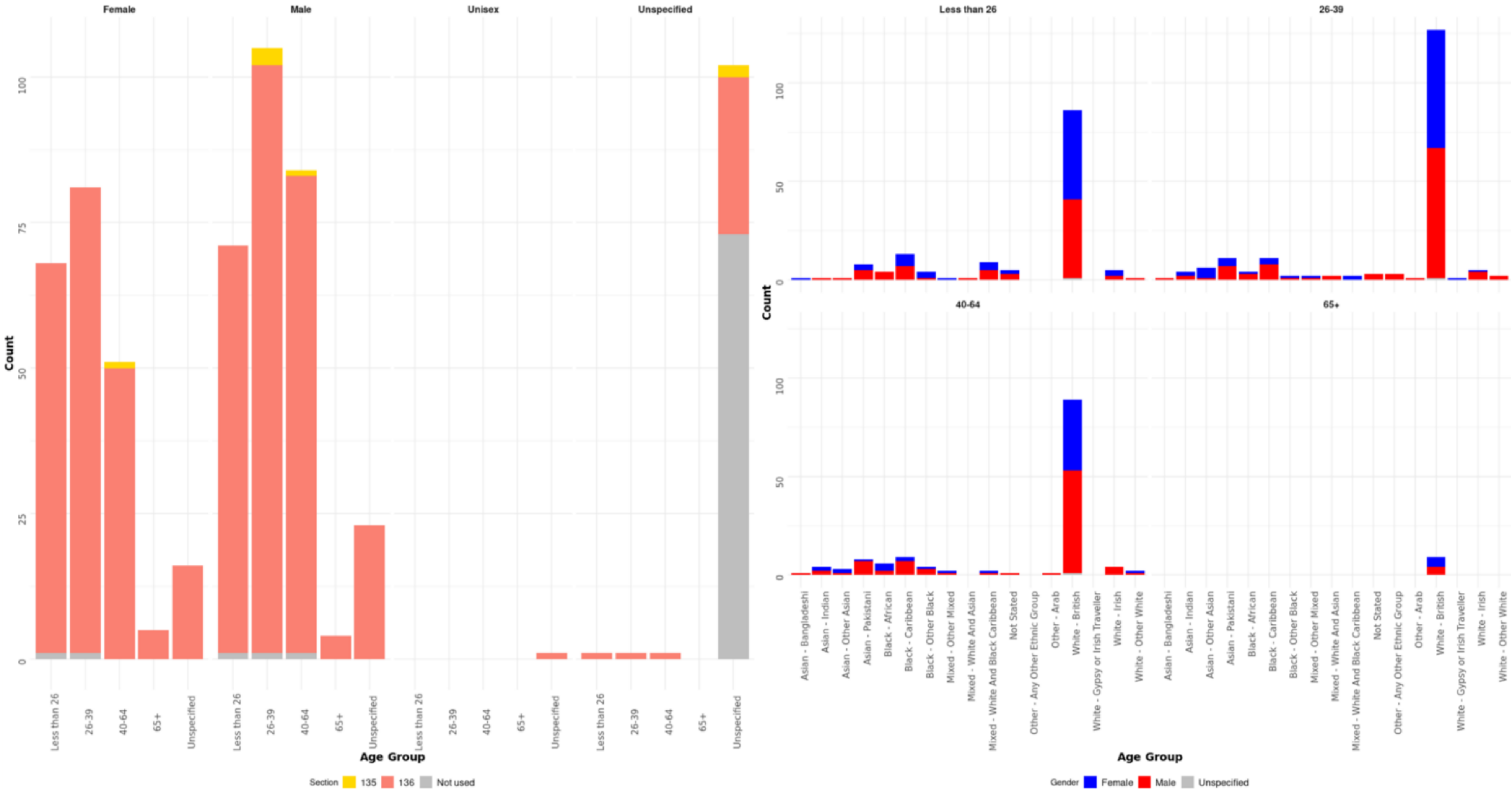


Figure 16 Demographic Information from the New Mental Health Forms

From Figure 16 we can see that males below 40 are the most frequent recipients of Sectioning (either 135 or 136) under the Mental Health Act. The ethnic group most frequently involved is White- British, though Pakistanis and African-Caribbean are showing an increase in the younger age groups. This perhaps gives notice of a change in attitudes in these communities as well as society as a whole.

Assessment Outcomes		Police High	Police Medium	Police Low
Place of Safety	**High**	17	18	6
Place of Safety	**Medium**	5	58	42
Place of Safety	**Low**	3	13	52

Figure 17 Assessments of Risk by Police & Place of Safety

Most helpfully, the data also includes the risk assessments by both the police and the Place of Safety. There is a high level of concordance between the two levels, though it appears that the police are less likely to use a high risk level and more likely to err on the side of *medium* risks.

AMHP or Place of Safety risk assessment	**Police risk assessment**	**Known to Mental Health Services: Missing entry**	**No**	**Yes**
No entry	**No entry**	368	2	9
No entry	**High**	0	0	3
No entry	**Medium**	4	2	4
No entry	**Low**	1	2	5
High	**High**	1	6	10
High	**Medium**	1	3	14
High	**Low**	0	1	5
Medium	**High**	0	1	4
Medium	**Medium**	0	13	45
Medium	**Low**	0	7	35
Low	**High**	0	1	2
Low	**Medium**	0	3	10
Low	**Low**	0	16	36

Table 18 Risk Assessments and Known Nominal

Data conclusions

The data available in WMP is substantial but is somewhat fragmented and the current analysis is hampered by changes in the systems used and the ongoing pandemic has had an impact on the data. The norms have been potentially shaken and the data from the past is not always comparable to that which is currently prepared and recorded. New information is becoming available but needs to link better to the main systems through golden identifiers and incident numbers as the names and dates are not firm enough to ensure the correct links. This will be an ongoing process but the seeds are present for a high degree of support for understanding the demand from those who are facing mental health issues.

Modelling

Having assessed and considered the data, this section looks briefly at the approach for modelling the incidents and crimes associated with mental health nominals. There are two particular models for a base line- those of incidents only and those that are converted into crimes. A second strain looks to forecast four weeks ahead (or a month). The baseline is determined by a set of regressions, which model the expected value of the outcomes using the other variables; in other words what would we expect if a ward had certain characteristics be they physical, custodial or temporal.

Baselines

A number of models without geo-spatial aspects were initially fitted for comparison. The geospatial aspects can be important as the fact that near things can show similarity can have statistical effects[iv]. The first geo-spatial model considered is that of a Besag (1975) model. This is a specific form of the (intrinsic) Conditionally Autoregressive (CAR or iCAR) model. This has been used in similar scenarios such as Marco et al. (2017) where a combination of calls to the police involving suicide was considered. This is extended to use the Besag, York & Mollié (1991) model. These models explicitly take into account the geo-spatial aspects of the data, which we have seen is important in the data.

Table 2 gives the specification of the models used along with the variables by grouping (the bold face Greek represents a vector of coefficients). The basic modelling approach was to use either a Poisson or Zero Inflated Negative Binomial with a number of different assumptions on the processes.

A number of variables were used having taken a moving average of the levels. This is to get an understanding of how the trends effect the levels of outcomes. *COVID* is a dummy variable for the lockdown period starting in April 2020. The variable with the coefficient, λ, is a rolling maximum of the mental health incidents and crime numbers over the past 6 months by ward as a proportion of the highest number of the same across the West Midlands. This seeks to compare the current level to a previous maximum relative to that of the region. This helps to highlight areas with consistently high levels of incidents or crimes associated with mental health issues.

The *MISPER*, *CUSTODY* & *CRIME* variables are groupings of the variables associated with each of these wider groups, for example *MISPER* includes variables such as the number of missing adults and *CUSTODY* the number of mental health associated detainees in the various custody blocks. The terms in *d* are other conditioning factors as reported in the Appendix. A number of models were used and compared.

Table 2 Model Specifications For Hierarchical Bayesian Models

Data Model

$$y_i \sim \begin{cases} Pois(\mu_{ij}) \\ ZeroInflNegBin(\mu_{ij}, p) \end{cases}$$

Process Model

$$\begin{aligned} \boldsymbol{g}(\mu_{ij}) &= (\alpha + \boldsymbol{\beta}^T X_{t-1} + \boldsymbol{\gamma}^T Crime \\ &\quad + \boldsymbol{\delta}^T Custody + \boldsymbol{\theta}^T Misper + \boldsymbol{\lambda}\frac{\max(y_{i,t-1})}{\max(y_{WM,t-1})} \\ &\quad + \psi COVID + \boldsymbol{\Xi}^T d_{it}) + (U_i + ward_i) + \epsilon_{it} \\ ward_i &\sim 0 + I_{Besag} ICAR(\boldsymbol{W}, \sigma^2_{sp}) + I_{BYM} BYM(\boldsymbol{W}, \sigma^2_{sp}, \sigma^2_{iid}) \\ U_i &\sim RW(y_{i,t-1}) + I_{Besag} RW(Month_t, \sigma_{Month}) \\ &\quad + I_{BYM} RW(Month_t \sigma_{Mth}) \\ I_{Besag} &= \begin{cases} 1 \text{ if Besag Model used} \\ 0 \text{ otherwise} \end{cases} \\ I_{BYM} &= \begin{cases} 1 \text{ if BYM Model used} \\ 0 \text{ otherwise} \end{cases} \\ \boldsymbol{g}(\bullet) &= \text{Canonical Link function for Generalised Linear Model} \\ &= \begin{cases} \log(\mu_{ij}) \text{ for Poisson Model} \\ \log\left(\frac{\mu_{ij}}{\mu_{ij}+\psi}\right) \text{ for Zero Inflated Negative Binomial} \end{cases} \end{aligned}$$

Parameter Model

$$\begin{aligned} (\sigma^2_{iid})^{-1} &\sim \log\Gamma(1, .01) \\ (\sigma^2_{Mth})^{-1} &\sim \log\Gamma(1, .01) \\ (\sigma^2_{sp})^{-1} &\sim \log\Gamma(1, 0.0005) \\ p &\sim \text{logit}(N(-1, 0.2)) \\ \exp(\psi) &\sim \Gamma(7^{-1}, 7^{-1}) \end{aligned}$$

The resultant best predicting models were a spatial count model, based on the Besag, York and Mollié (1991) approach (BYM) and a spatially independent exponentially weighted moving average model (EMA) as an additional model. These are best used together, the BYM model deals with the more subtle spatial changes across the wards, which can have an impact. The underling distribution beneath this model is a zero-inflated negative binomial as there are a number of areas where the number of zeros is higher than would be expected and the statistical properties of the simpler models are found not to hold. The EMA model picks up the overall trends in each ward. Some wards are isolated and so the time series model is sufficient.

Outcomes: Mental Health Incidents

The models overall tell a number of important stories. The number of service providers is consistently a positive factor in the number of incidents with mental health associations. The number of anti-social crimes in a month and the number of criminal damage crimes all have a weak positive impact on the number of incidents. Likewise harassments are also positively related to the number of incidents. Violent crime has a strong positive effect on the incidents irrespective of the specification. Theft however is inversely related. These are, with the exception of theft, as one might expect.

The impacts are small in magnitude as the number of incidents is itself relatively small and thus the size reflects the relative sizes. The information criteria all suggest that the BYM model is the best fit and this itself implies that the geo-spatial elements are driving much of the result. This is giving us an indication of what makes for a 'normal' level; areas with more providers, more damage and harassment tend to be areas with higher levels of mental health demand. Much of the explanatory power is based on the geo-spatial element.

Some of the results were robust to the choice of model, though the zero inflation element tended to reduce the impact of some of the variables. The comparisons of the variable levels is available in Table F &G. It is noticeable that drugs are a negative impact on the mental health incidents in the wards. It is possible to consider the variables' effects graphically by looking at the distributions; the Figures presented in the Appendix give the posterior density for the estimated coefficients, where these are centred away from zero and zero is outside the interval we can say that there is some effect. It appears that there are some natural dynamics that are present in the simpler models that the BYM model subsumes in the structure of the geospatial model. Many of the outcomes as described by the variables in these simpler models are as one would expect, such as average missing persons levels for both children and adults has a positive impact but the lagged variables is negative. This brings a cyclical element to the time series.

The ICIS data's impact is varied with again the simpler models both Poisson and zero inflated negative binomial models both reporting a positive coefficient for the Perry Barr levels and a negative impact for Coventry Central. The Aston Mental Health Act referrals only have a delayed impact on the incidents levels in wards. COVID-19 appears to have a negative impact, which may be due to the short data series involving the lockdown and that this might have a more positive impact later. The rolling maximum over the previous 6 months generally have a positive impact, though stronger with the Poisson than the zero inflated model. This suggests that there is some ongoing inertia in the incidence of mental health incidents.

An example of the BYM Zero inflated model is presented here with all the estimates and posterior densities for the coefficients presented in the Appendix.

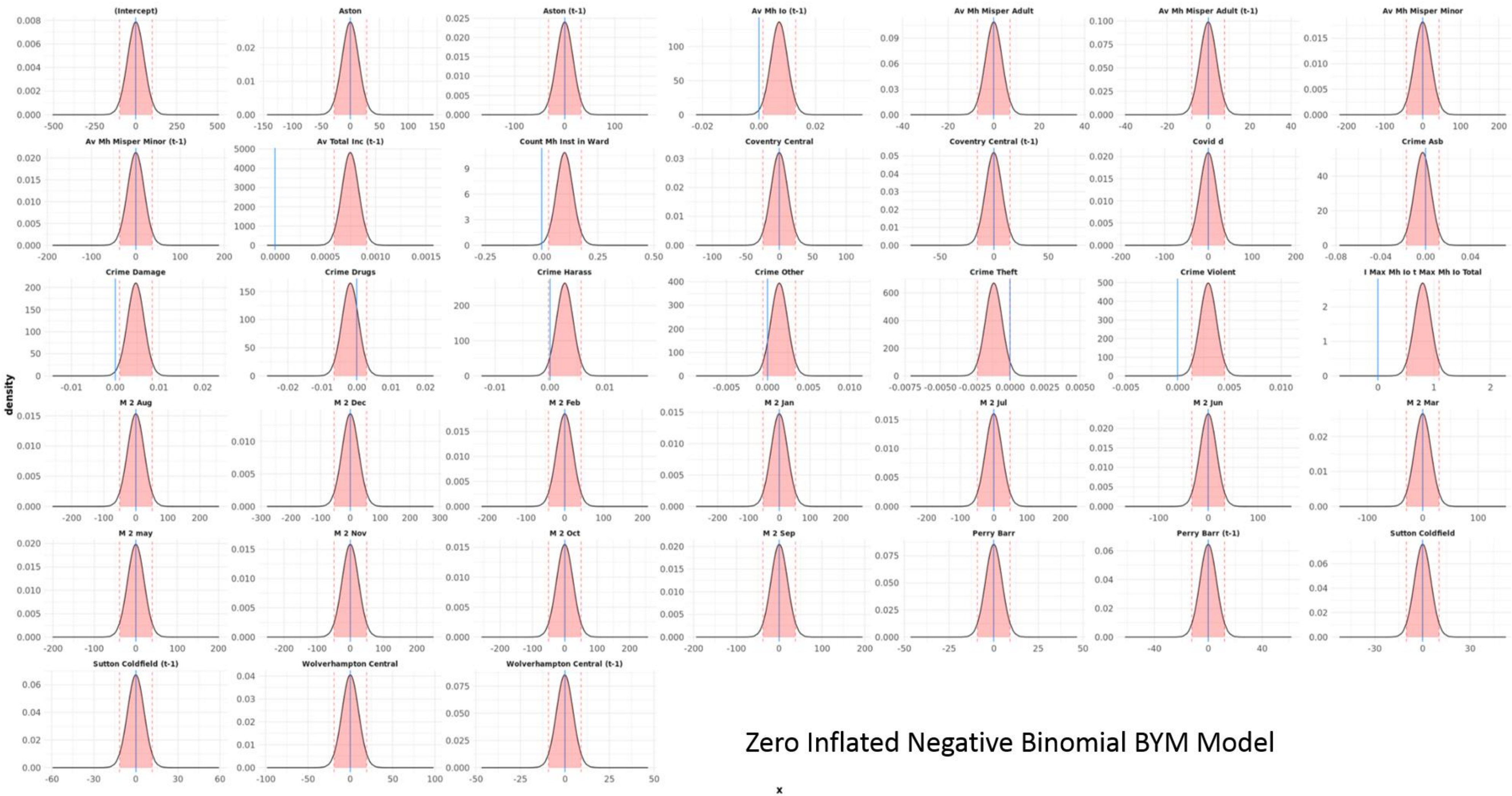


Figure 19 Posterior Densities for Estimated Coefficients Incidents

Outcomes: Mental Health Crimes

In addition to considering the demand from purely incidents, crimes were also considered. These crimes are those where a mental health dimension has been reported. The models were set up in the same manner with the only difference being that crimes were the dependent variable and that these were described as a random walk for the time series element. Results are presented in the Appendix, with only salient points being discussed. The Poisson models have a parallel set of results in terms of the changing emphasis as the models' assumptions change.

The simpler and Besag models show a positive impact on mental health associated with crimes from the previous level of this variable. Both of these models show similar patterns with respect to missing persons with mental health issues, previous levels of both children and adults have a negative coefficient, so that these are associated with reductions in the number of mental health crimes, whereas the current levels of children missing in that period is positive (if small for the Besag model) so will be associated with increasing crimes associated with mental health.

The more complex model reduces the importance of many of the variables and in fact the impact of the last six months crimes switches from a positive coefficient (and impact) to a negative one. The average number of incidents over six months (lagged) has a stable positive relationship with the level of mental health crimes. Interestingly the count of mental health services providers remains positive irrespective of these different models, again suggesting a degree of locality or comfort associated with such areas. Violent crime in general is positively related with crimes associated with mental health across the models, whereas theft has a negative relationship. The previous peak variable is consistently positive suggesting that if an area is seeing a lot of mental health crime on average over the last 6 months relative to the region, then there will tend to be a continuation or increase.

The zero inflated models have a similar set of coefficients to the extent that the general direction of all the relevant variables is the same. Thus the underlying variables are considered as robust. The PIT diagnostics suggest over dispersal in the Poisson models. These are presented in Figure 36, and the zero inflated negative binomials tell a similar story as the incident only. There is generally little over-dispersion once the zero-inflation is accounted for. The localised DICs suggest that the models are very similar with better fits towards the west and the north of the region, though the more populous areas of Birmingham and Coventry might explain the higher local DIC statistics. The DIC maps in **Error! Reference source not found.** show that the models demonstrate general clustering as was found elsewhere, with swathes of darker and lighter colours in the WMP area suggesting localised effects not captured by the models. These show areas where the models are consistently under or over estimating the data and in doing so, they highlight areas worthy of extra consideration by WMP and its officers.

Geo-Spatial Predictive Models

The predictive model is an extension of the main model. It looks to predict either incidents or crimes where there is a mental health dimension. The prediction is made against the August outcomes as this was the last period where the data was complete. The outcomes of the predictions are compared to these using Root Mean Squared Error and Mean Absolute Error. These measure the deviations from the outcomes by the predictions.

The outcomes are shown in Figure 20 & Figure 21 for incidents only. This shows more around the main centres of population. The estimates of the number of incidents over-estimates by 6.5 (using the median) and 10 (with the mean) using the absolute error measure. For crimes, the mapped outcomes are shown in Figure 22 & Figure 23. We can compare the metrics across the families of models to again consider the best model. The absolute errors show the over-estimation of the models compared to the actual outcomes for August 2020.

The outcomes can be summarised looking at these errors. Regressing the outcomes on a constant gives the expected error and a standard error associated with it. It is noticeable that the crimes are generally predicted more accurately than the incidents. This is most probably due to the clearer definition of the incident once a crime has been determined to have taken place and that in an incident there are a number of possible 'definitional' issues. This is to consider the overlap and performance of the models, rather than for any explanatory purposes.

We can see that there is some differences in the models' predictive accuracy. These are summarised in the table below using a regression to allow us to compare across the models with the Besag Zero Inflated Negative Binomial being used as the base against which all other models are measured.

Table 3 Model Absolute Errors for Crimes and Incidents Associated with Mental Health

			Quantiles				
Incidents	Mean	SD	2.50%	25.00%	50.00%	75.00%	97.50%
Intercept (Mean)	14.9	0.8	13.3	14.3	14.9	15.4	16.5
Besag Zero Inflated Negative Binomial	-3.9	1.1	-6.1	-4.6	-3.9	-3.1	-1.6
BYM Poisson	-7	1.2	-9.4	-7.8	-7	-6.2	-4.8
BYM Zero Inflated Negative Binomial	-6.2	1.2	-8.4	-6.9	-6.2	-5.4	-3.9
Simple Poisson	-5.8	1.2	-8.1	-6.6	-5.8	-5	-3.5
Simple Zero Inflated Negative Binomial	-4.5	1.1	-6.7	-5.2	-4.5	-3.7	-2.2
σ	11.7	0.2	11.3	11.6	11.7	11.9	12.2

			Quantiles				
Crimes	Mean	SD	2.50%	25.00%	50.00%	75.00%	97.50%
Intercept (Mean)	1.0	0.1	0.8	0.9	1.0	1.0	1.2
Besag Zero Inflated Negative Binomial	0.7	0.1	0.5	0.6	0.7	0.8	1.0
BYM Poisson	0.0	0.1	-0.3	-0.1	0.0	0.1	0.3
BYM Zero Inflated Negative Binomial	-0.3	0.1	-0.5	-0.3	-0.3	-0.2	0.0
Simple Poisson	0.0	0.1	-0.3	-0.1	0.0	0.1	0.2
Simple Zero Inflated Negative Binomial	0.8	0.1	0.5	0.7	0.8	0.8	1.0
σ	1.3	0.0	1.2	1.3	1.3	1.3	1.4

NOTE: the more negative the number in the "Mean" column the better the model predicts.

The underlying message from all these models, whether or not they are the best predictor, is that the expectation is that there is a gradation of incidents relating to mental health, driven in part by population centres and in part by the presence of mental health services and the history of that area over the last 6 months. Similarly the prediction of crime levels associated with suspects and defendants with mental health issues is also clustered. It is generally low across most wards, though there is a line across the region centred on Birmingham running from the south-west to the north east that shows higher levels with the north-western 'incident only' area not being highlighted. There is a similar grouping around Coventry, though this more directly reflects the incident predictions.

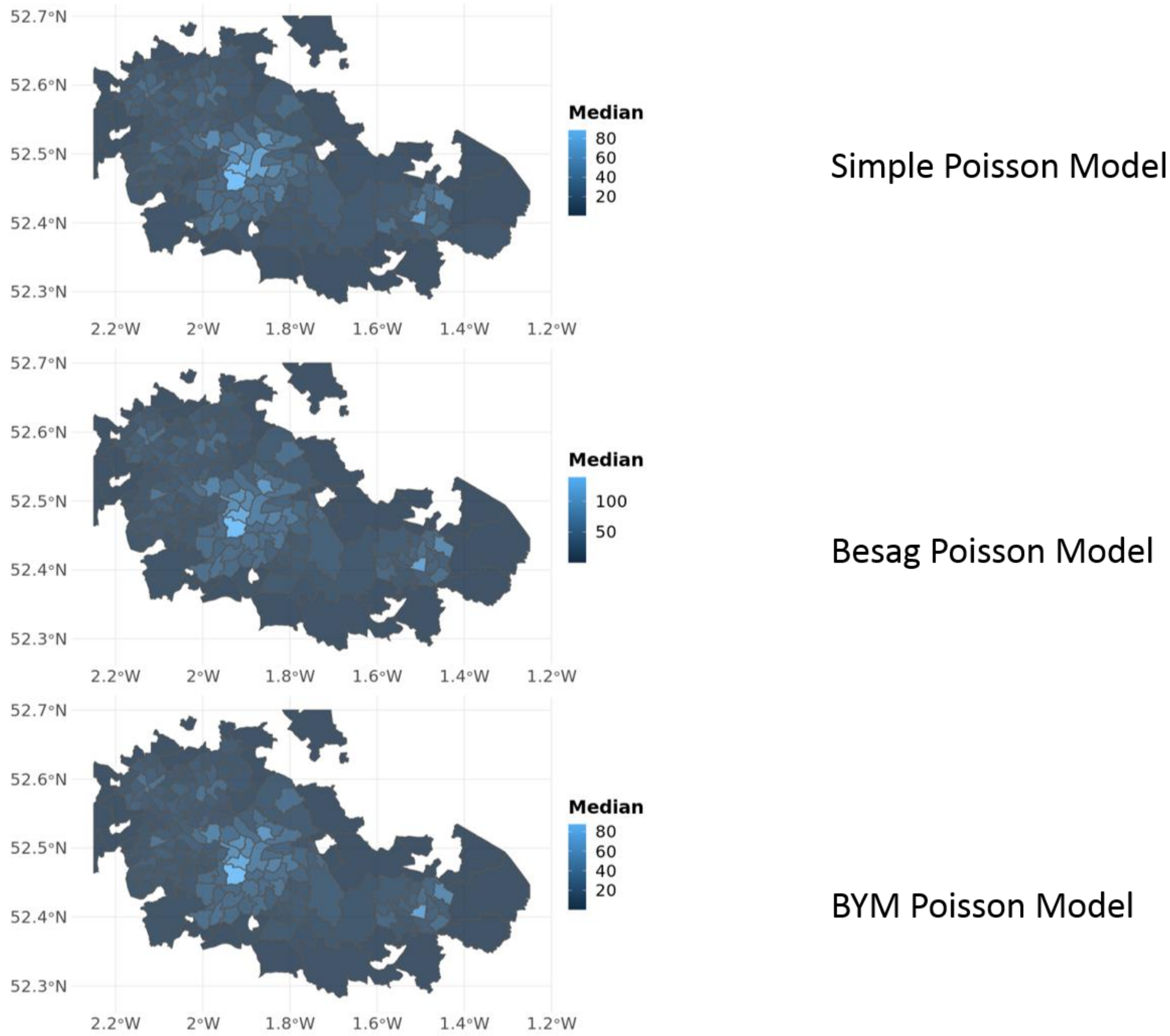
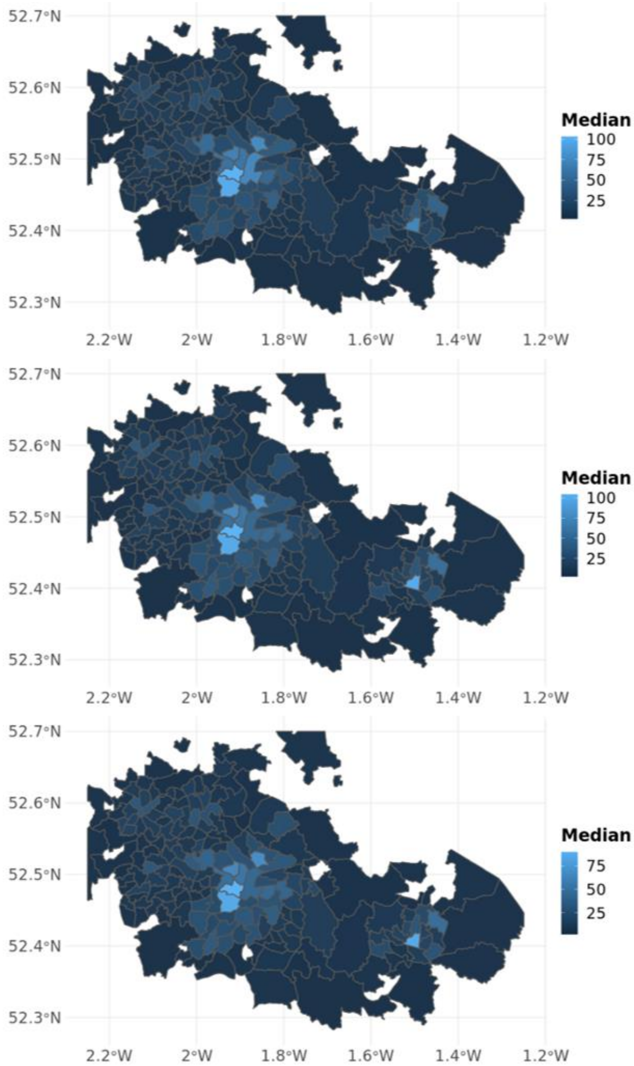


Figure 20 Incident Only Predictions (Poisson models)



Simple Zero Inflated Negative Binomial Model

Besag Zero Inflated Negative Binomial Model

BYM Zero Inflated Negative Binomial Model

Figure 21 Incident Only Predictions (Zero Inflated Negative Binomial Models)

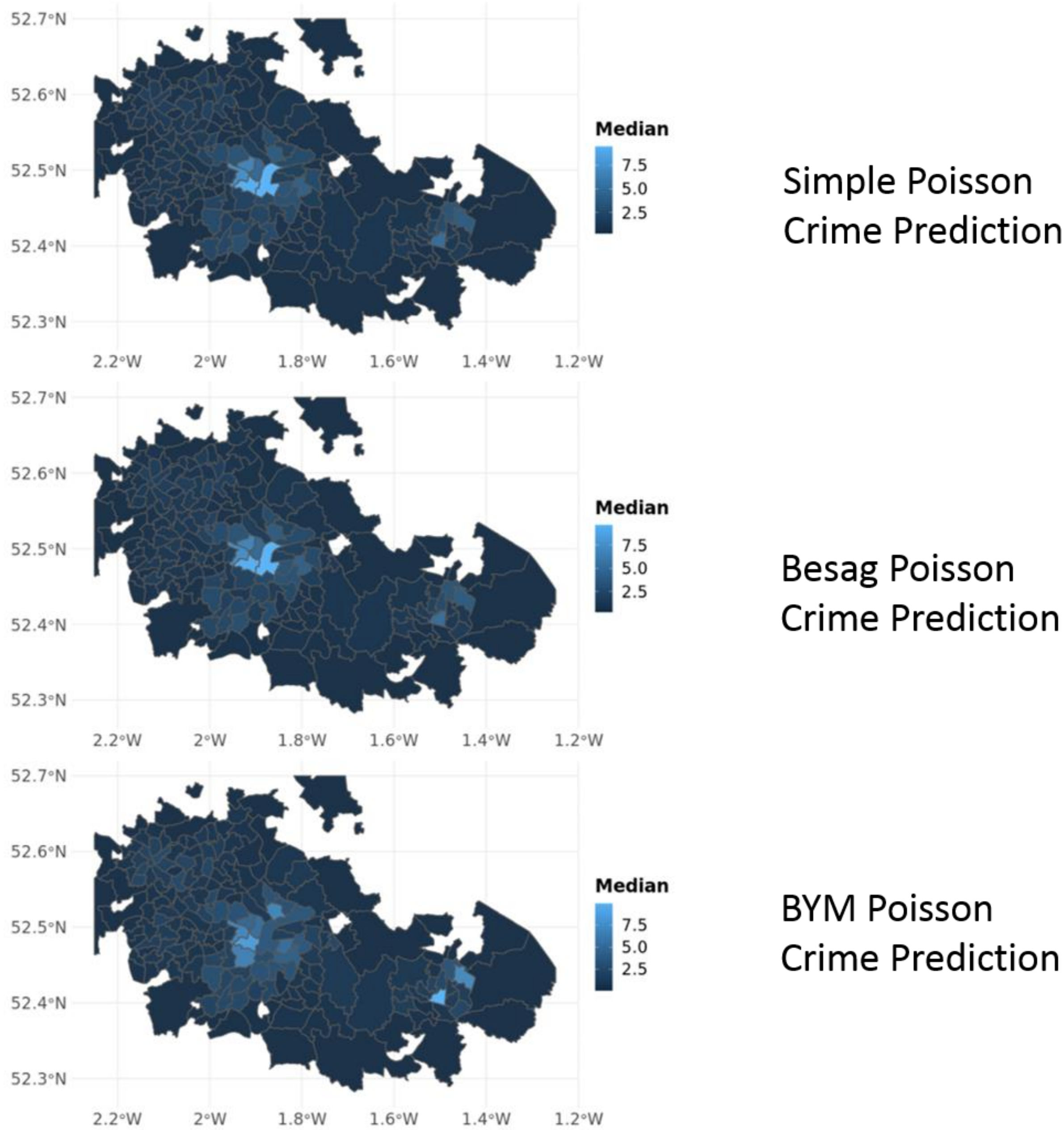


Figure 22 Crimes Predictions (Poisson Models)

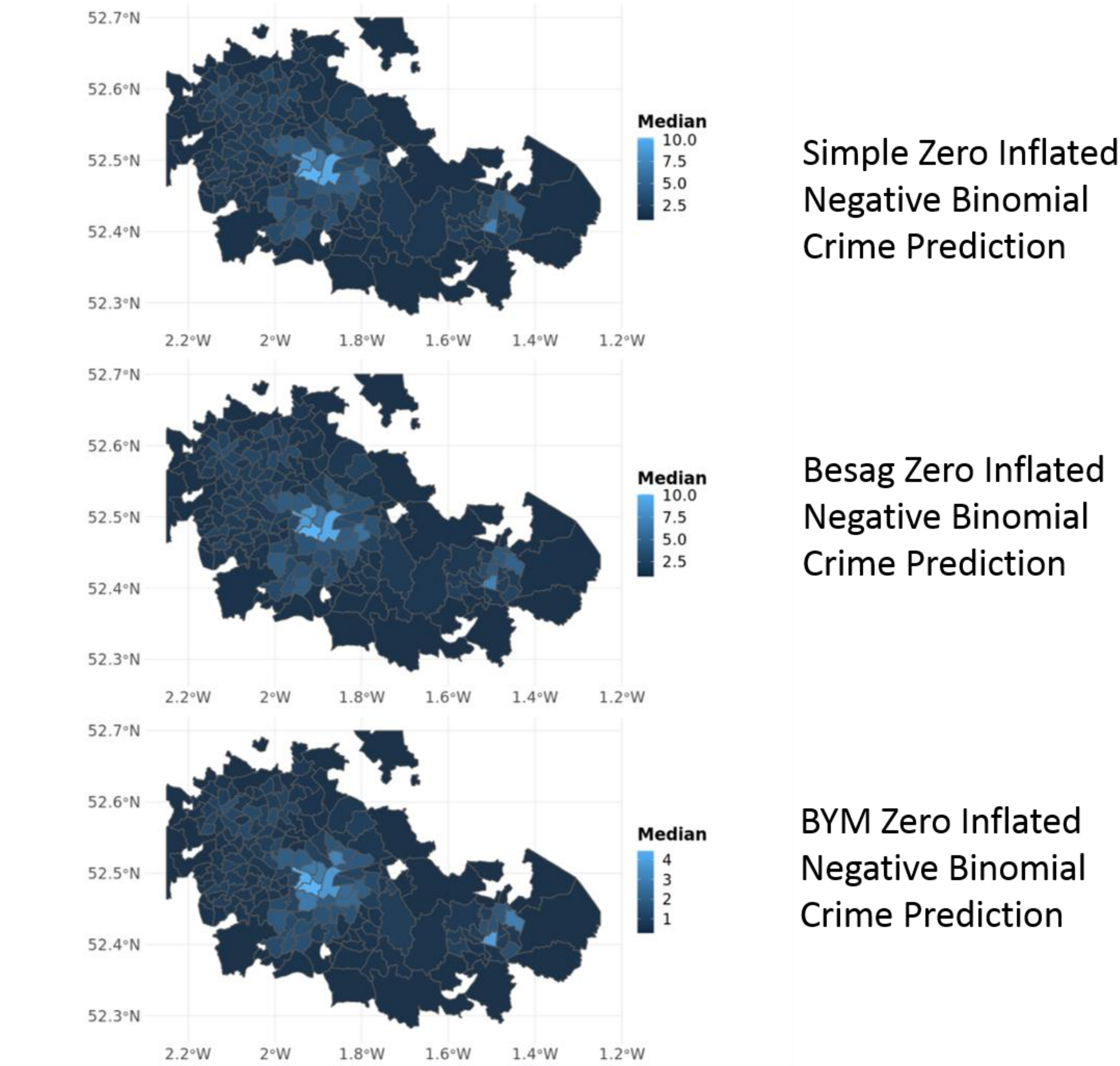


Figure 23 Crime Predictions (Zero Inflated Negative Binomial Models)

Model Performance

The geo-spatial models perform best with both Poisson and Zero Inflated models performing well when considering incidents, though the zero-inflated models for crimes are generally preferred. It should be noted that this is an aggregation and as such should be used with caution as can be seen in Figure 24 Density of Absolute Errors which shows that though there is a significant clustering, there are a number of large outliers.

These metrics suggest that on the whole these models have a reasonable predictive power, though there are some areas where this does not hold. It would be worth considering the partner data for these areas to see if there is something specific that exists here which is not currently understood using the WMP data.

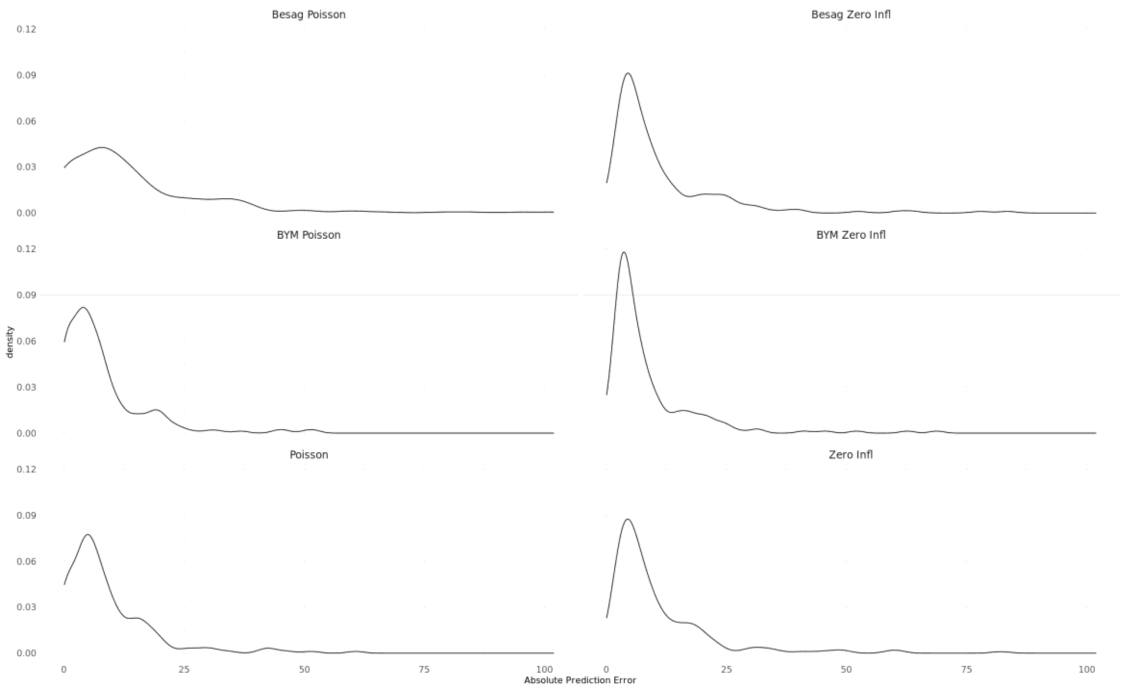


Figure 24 Density of Absolute Errors Incidents Only

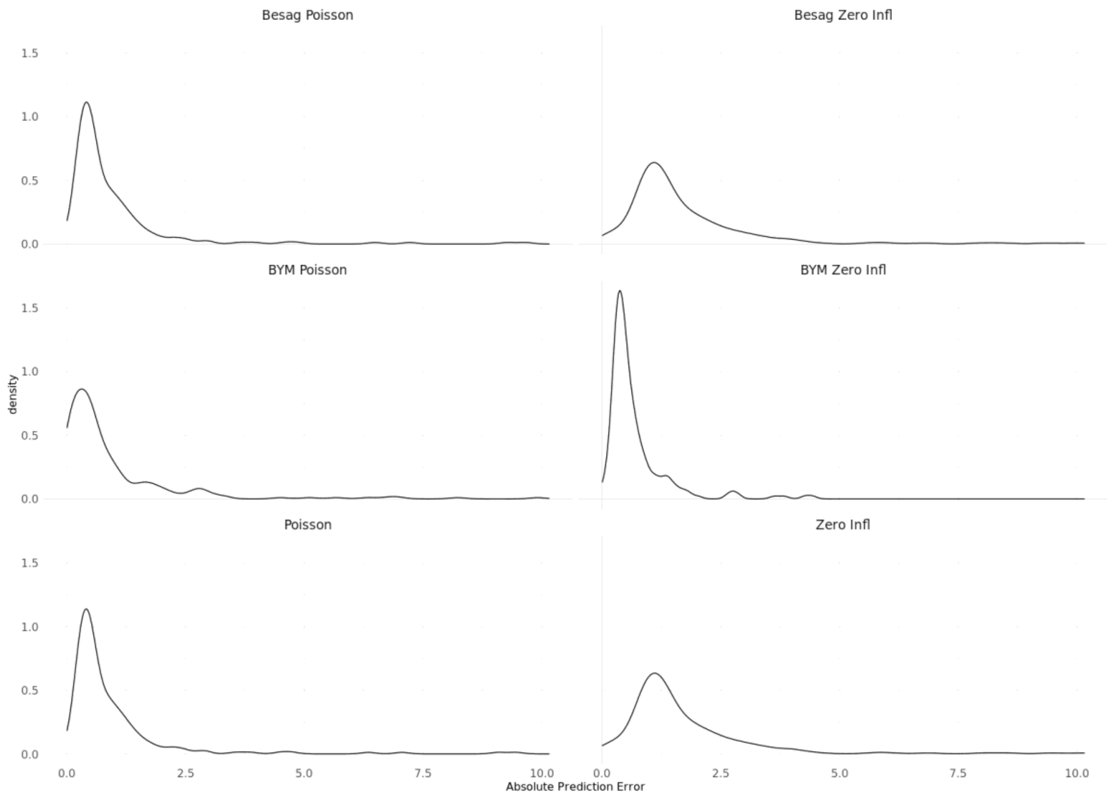


Figure 25 Density of Absolute Errors for Crimes

Time Series Smoothing Exponential Moving Average

Adding an exponential moving average or exponential smoothing is a simple method of looking at the wards in isolation and to consider the time series dynamics. One advantage of this type of approach is the speed with which it can be calculated and projected. However, the main issue with this is that each ward is in isolation, which is clearly a substantial assumption: it is suggesting that people a) know where ward boundaries are b) do not cross them. Further it does not give the possibility to move away from 0. These exponential smoothers are a simple benchmark.

These are estimated for the period up until August 2020 and then forecast that month as before. An automatic estimator was used to select the smoothing parameter; this was estimated to be small suggesting a high degree of smoothing.

The predicted outcomes are compared to the outcomes with the geospatial models. The projections are presented below in the two maps. The mean absolute errors for the predictions were 6 for the incidents (median of 4.4) and 0.74 for the crimes (median of 0.6). These numbers suggest that these are good models, despite their simplifications and are worth including in the output. Indeed the maps are almost identical and so can be used in conjunction with the expert knowledge to suggest a potential area for increasing or decreasing demand. Unlike the geo-spatial models, the models here also highlighted the north-western area as potentially a higher crime area, though it gave that area less emphasis when it comes to incidents.

It should be noted though that the lower bounds in most of the ETS predictions were less than zero.

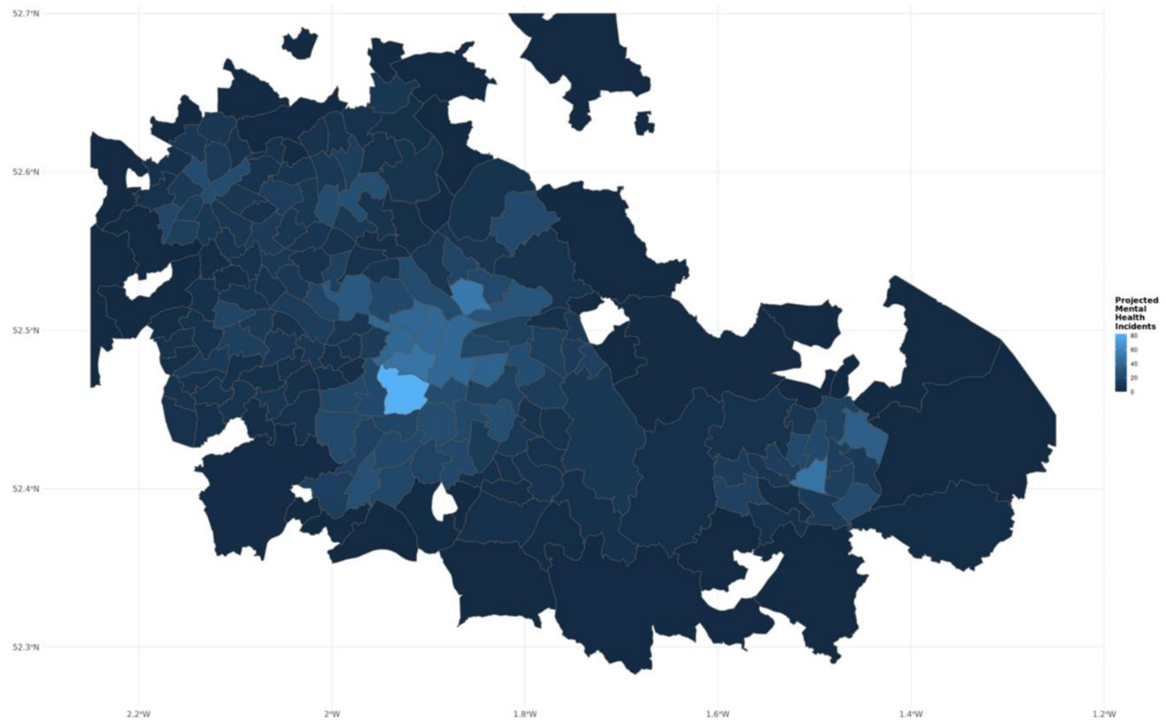


Figure 26 Predicted Mental Health Incidents (ETS)

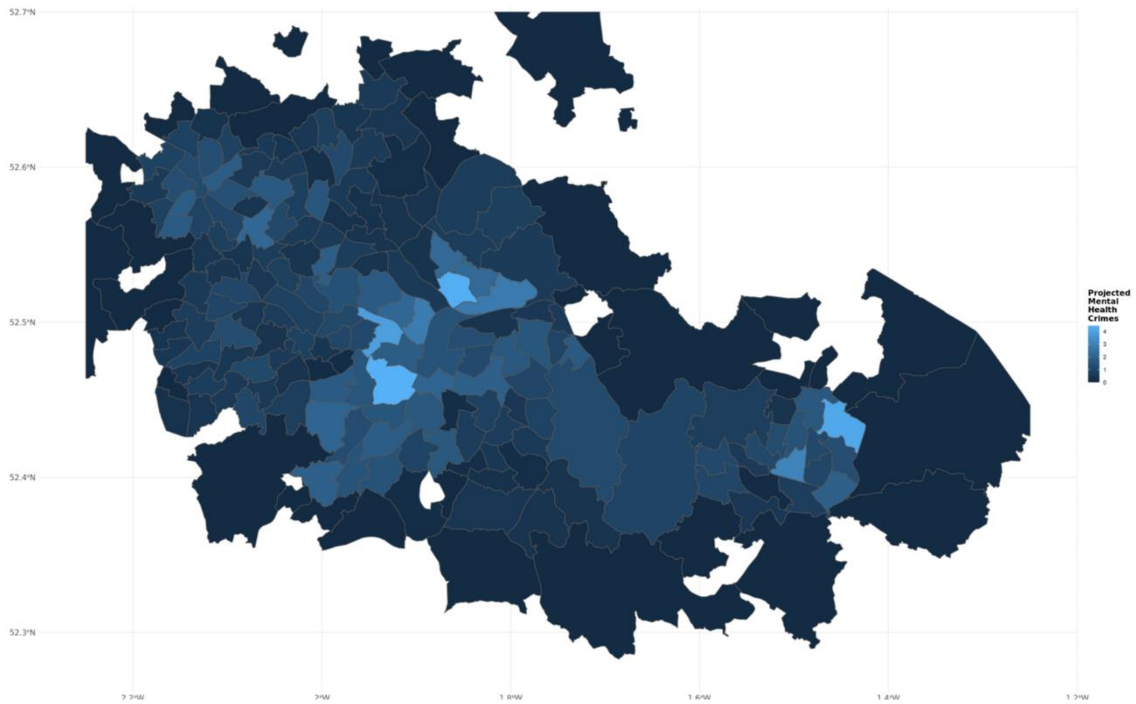


Figure 27 Predicted Mental Health Crimes (ETS)

Summary

The models and data considered here show that there is considerable data available to WMP, though much of it is young and as such has too short a time period to use in models as yet. Further the pandemic has had an impact on the normal demand. This will mean that there is an opportunity for further investigation at a later stage and to monitor these models in order to see their usefulness over the coming months. The data and models give predictions that map on to population centres and areas where there would appear to be more issues. However the framework is in place to develop a further set of models based on this and partner data.

Currently the predictions are based on geo-spatial and time series models are consistent with each other in general terms. There is a clear set of clusters around the region where we would expect to see more incidents and crimes that would benefit from the presence of the triage groups. Clearly more specific understanding of these areas will help guide their deployment further and this is an obvious role for the partner and new data as it becomes available.

There is a great deal of rich information that is currently not effectively linked to the main WMP systems. This would be the logical next step along with the use of partner data in order to understand the impact mental health has on the demands for WMP service provision. This would lead to the potential of better resourcing and focusing the mental health resources to those areas where there is greatest demand and highest levels of impact for WMP.

Bibliography

Besag, Julian. 1975. “Statistical Analysis of Non-Lattice Data.” *Journal of the Royal Statistical Society. Series D (the Statistician)* 24 (3). [Royal Statistical Society, Wiley]: 179–95. http://www.jstor.org/stable/2987782.

Besag, Julian, Jeremy York, and Annie Mollié. 1991. “Bayesian Image Restoration, with Two Applications in Spatial Statistics.” *Annals of the Institute of Statistical Mathematics* 43 (1). Springer: 1–20.

Blosnich, John R, Mary C Marsiglio, Shasha Gao, Adam J Gordon, Jillian C Shipherd, Michael Kauth, George R Brown, and Michael J Fine. 2016. “Mental Health of Transgender Veterans in US States with and Without Discrimination and Hate Crime Legal Protection.” *American Journal of Public Health* 106 (3). American Public Health Association: 534–40.

Greene, Karen Shalev, and Carol Hayden. 2014. “Repeat Reports to the Police of Missing People: Locations and Characteristics.” University of Portsmouth.

Heckman, James J. 1977. “Sample Selection Bias as a Specification Error (with an Application to the Estimation of Labor Supply Functions).” National Bureau of Economic Research.

HMICFRS (2018). “Policing and Mental Health: Picking Up the Pieces.” London: HMICFRS. Report number: ISBN: 978-1-78655-741-4. Available from: https://www.justiceinspectorates.gov.uk/hmicfrs/wp-content/uploads/policing-and-mentalhealth-picking-up-the-pieces.pdf

Lorenc, Theo, Mark Petticrew, Margaret Whitehead, David Neary, Stephen Clayton, Kath Wright, Steven Cummins, Amanda Sowden, and Adrian Renton. 2014. “Crime Fear of Crime and Mental Health: Synthesis of Theory and Systematic Reviews of Interventions and Qualitative Evidence.” *Public Health Research* 2 (2): 1–398.

Marco, Miriam, Antonio López-Quílez, David Conesa, Enrique Gracia, and Marisol Lila. 2017. “Spatio-Temporal Analysis of Suicide-Related Emergency Calls.” *International Journal of Environmental Research and Public Health* 14 (7). MDPI AG: 735. https://doi.org/10.3390/ijerph14070735.

McCullagh, P., and J.A. Nelder. 1989. *Generalized Linear Models, Second Edition*. Chapman and Hall/CRC Monographs on Statistics and Applied Probability Series. Chapman & Hall. http://books.google.com/books?id=h9kFH2_FfBkC.

All Party Parliamentary Group for Runaway, Missing Children, and Adults. 2018. “Inquiry into Safeguarding Missing Adults Who Have Mental Health Issues.”

Riebler A, Sørbye SH, Simpson D, Rue H. “An intuitive Bayesian spatial model for disease mapping that accounts for scaling”. Stat Methods Med Res. 2016 Aug;25(4):1145-65. https://doi: 10.1177/0962280216660421. PMID: 27566770.

Rogers, J.P., Chesney, E., Oliver, D, Pollak, T.A., McGuire, P., Fusar-Poli, P., Zandi, M.S., Lewis, G. and David, A.S. 2020. “Psychiatric and neuropsychiatric presentations associated with severe coronavirus infections: a systematic review and meta-analysis with comparison to the COVID-19 pandemic” *Lancet Psychiatry 7, 611-27* https://doi.org/10.1016/S2215-0366(20)30203-0

Sowerby, Amy, and Stuart DM Thomas. 2017. “A Mixed Methods Study of the Mental Health and Criminal Justice Histories of Missing Persons.” *Police Practice and Research* 18 (1). Taylor & Francis: 87–98.

Spiegelhalter, D.J., Best, N.G., Carlin, B.P. and Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64(4), pp.583-639.

Spiegelhalter, David J., Nicola G. Best, Bradley P. Carlin, and Angelika van der Linde. 2014. “The Deviance Information Criterion: 12 Years on.” *Journal of the Royal Statistical Society. Series B (Statistical Methodology)* 76 (3). Pp.485–93. http://www.jstor.org/stable/24774528.

Weisburd, David, Breanne Cave, Matthew Nelson, Clair White, Amelia Haviland, Justin Ready, Brian Lawton, and Kathleen Sikkema. 2018. “Mean Streets and Mental Health: Depression and Post-Traumatic Stress Disorder at Crime Hot Spots.” *American Journal of Community Psychology* 61 (3-4): 285–95. https://doi.org/10.1002/ajcp.12232.

Wheeler, D. C., Hickson, D. A., & Waller, L. A. 2010. “Assessing Local Model Adequacy in Bayesian Hierarchical Models Using the Partitioned Deviance Information Criterion”. *Computational statistics & data analysis*, 54(6), 1657–1671. https://doi.org/10.1016/j.csda.2010.01.025

World Health Organization. 2001. “Gender disparities in mental health”. Geneva: World Health Organization.

Technical Appendix

The models used here are based on count data. Rather than using the normal form of regression it uses a form of model based upon a discrete, non-negative value. The simplest of these is the Poisson model. In this model, the expected value and the variance of the count variable (the number of incidents in this situation) are equal. This is obviously rarely the case, however it is normally used as an initial investigation point as the model allows a simple relationship between the variables.

If the variance and mean of the data do not coincide, then the model is said to be over (or under) dispersed. This is commonly caused by heterogeneity in the units of observation (i.e. the wards). This will mean that the inference from the Poisson approach will be limited in its applicability. In light of this a generalisation of the Poisson is used. This is the negative binomial regression, where the variance is no longer constrained to be equal to the mean of the counts. An extra parameter that measures the dispersion is estimated and can be compared to the value of 0 which would be equivalent to the Poisson model.

These two models are generally useful for count data, however in the situation as considered here, there is an alternative; that of zero inflation. To understand this, one must appreciate that the previous two approaches are estimating the number of occurrences of an event. It is legitimate to expect zero cases sometimes. However in some cases, there are reasons why this zero event might be increased for reasons not involved in the relationship but by its very nature. These are sometimes called structural zeros. The literature often gives example of child births in older women, HIV incidents where there is no sexual activity or the like. This might also be applicable in the cases considered here. In order to take this into account, the structural zeros are modelled as a separate event with an associated probability. One can see the differences between the three approaches in Figure 28. The zero-inflated version looks a more applicable approach as many places are simply without the variable of interest.

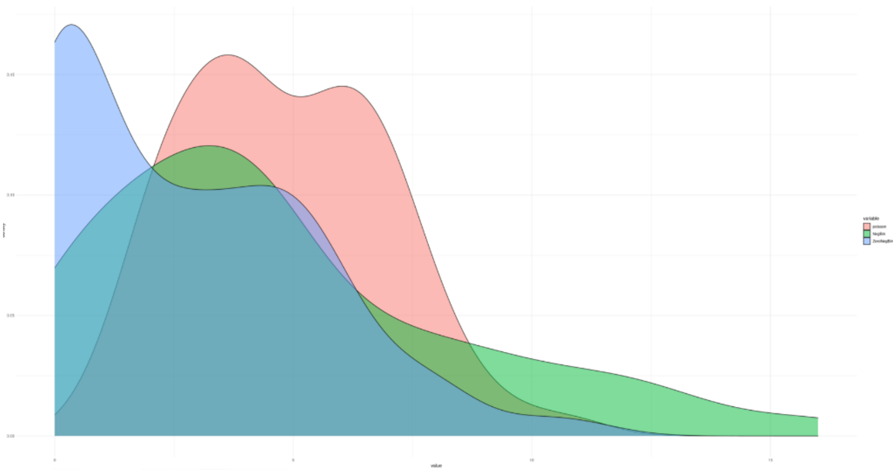


Figure 28 Comparison between Poisson, Negative Binomial & Zero Inflated Negative Binomial Distributions

The Poisson & Zero Inflated Negative Binomial models are estimated using maximum likelihood. The likelihoods are given by:

$$LogL_P = \sum\left(y\theta^T x - e^{\theta^T x} - \log(y_i!)\right)$$

$$LogL_{ZNB} = \sum y_i \log\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right) - \frac{1}{\alpha}\log(1+\alpha\mu_i) + \log\Gamma\left(y_i + \frac{1}{\alpha}\right) - \log\Gamma(y_i+1) - \log\Gamma\left(\frac{1}{\alpha}\right)$$

Where $\mu_i = \exp(x^T \beta)$

These models are used in conjunction with a number of specifications for the geo-spatial relationships in the data in addition to a simple model to compare against.

The Besag (1975) model is a form of Bayesian spatial and hierarchical model. The spatial process is derived from the Hammerley-Clifford Theorem which links the conditional distribution of particles given neighbouring particles and that of the global specifications. This model uses an improper prior over the spatial characteristics, whereas the BYM model (1991) has a combination of the Besag model and an iid Gaussian model for the spatial elements.

The Besag model (following the description of Riebler et al. 2016) uses a conditional distribution for the spatial element of the random effects of the form

$$u_i \mid u_{-i}, \tau_u \sim N\left(\frac{1}{d_i}\sum_{j\sim i} u_j, \frac{1}{d_i}\frac{1}{\tau_u}\right)$$

Where *i~j* denotes that *i* and *j* are neighbouring areas, *d* is the number of neighbours with size *u* and $\tau_u = \sigma_u^{-1}$, the precision associated with *u*. This gives rise to the joint distribution

$$u \mid \tau_u \sim N\left(0, \frac{1}{\tau_u}\mathbf{Q^{-1}}\right)$$

Where **Q** is the precision matrix of the data where

$$\mathbf{Q}_{ij} = \begin{cases} \boldsymbol{d_i} & \text{where } \boldsymbol{i = j} \\ \mathbf{-1} & \boldsymbol{i \sim j} \\ \mathbf{0}, & otherwise \end{cases}$$

The BYM model relaxes the restriction of the no spatial variability in the geo-spatial components. This gives an unstructured element which allows for the variability. The effect of this is to modify the covariance matrix of the spatial effect:

$$Var(\epsilon|\tau_u, \tau_v) = \tau_v^{-1}\mathbf{I} + \tau_{\boldsymbol{u}}^{-\mathbf{1}}\mathbf{Q}^{-}$$

Where *v* is a normally distributed random variable with variance $\tau_v^{-1}\mathbf{I}$ & $\mathbf{Q}^{-}$is the generalised inverse.

Modelling Issues

In order to deal with potential time series issues, an extra latent variable specified as a random walk of order 1 was used with the lagged dependent variable. It is using a Gaussian prior for the increments. An initial investigation using an AR(1) rather than a random walk, but the ρ parameter converged to a value of 1, i.e. integrated and thus the random walk was applicable. In order to model the spatial aspects, a neighbourhood (binary) weighting matrix was calculated and used in the formulation of the models.

The models are all count based and thus the Poisson & negative binomial families are used. One issue with the Poisson is the restriction on the dispersion. In order to ascertain how much of a problem this is, a dispersion estimate is calculated and compared to that of 1000 simulations. In light of this expected issue, negative binomial models and zero inflated negative binomials were also fitted. These relax the dispersion restriction and also take into account the potentially large number of zeros in the data.

Further diagnostic tools are also used. The Probability Integral Transformation (PIT) is used to look at the goodness of fit, in addition to the usual credible intervals for the coefficients and information criteria. The PIT uses the transformed residuals to those of an uniform distribution, which is a well-established result. The deviation of the transformed data from the Q-Q plot of the uniform distribution. As a metric, the area under the curve, relative to the 45◦ line is calculated in both value and absolute terms. A smaller value of both of these suggests that the model fits well. The absolute value is useful as it is asymmetric- the areas both and below the 45◦ line *cannot* cancel out. Heteroskedasticity in count models is inevitable, though the use of the generalised linear model (McCullagh (1989)) takes this into account, with overdispersion being a problem for Poisson models, though not for negative binomial based models. There is a juxtaposition between including a large number of fixed effects (such as a dummy for each ward) and the parsimony of the model. This is reflected in the information criteria (eg Spiegelhalter et al. (2014)). In light of this, wards are generally included as random effects and modelled using geo-spatial approaches such as the Besag (1975) and BYM (1991) approaches.

The Deviance Information Criteria is calculated for all models and the localised measure is also used to map the data to spatial polygons to assess where the model does not fit well (following Wheeler (2010)). The headline DIC is the sum of the local measures over each observation. By considering these at an observational level (and averaging over time), it is possible to see where the model has systematically under performed either by over or under-predicting systematically.. In other words areas where the mental health demand was different than what was expected and areas where there is a degree of systematic problem or pattern in the outputs. It should be noted that areas with higher population or demand in general will tend to have higher DICs and so larger DICs in these areas, such as Coventry or more populous parts of Birmingham should be expected. Irrespective of this, the DIC map can be used as a further signal of areas where there might be a problem in the coming period. Using the DICs we can look to investigate the role of new, additional variables from for example partner agencies that could increase the power of the models. This is a novel use of these metrics in policing.

Estimates of Coefficients Incident Models

Table 4 Estimates of Poisson Models for Mental Health Incidents Only

Simple Model	**Mean**	**SD**	**0.025 Quant**	**Median**	**0.975 Quant**	**Mode**
(Intercept)	0.999	0.11	0.783	0.999	1.215	0.999
COUNT MH INST IN WARD	0.055	0.007	0.042	0.055	0.068	0.055
CRIME ASB	0.001	0.005	-0.01	0.001	0.011	0.001
CRIME DAMAGE	0.007	0.001	0.005	0.007	0.01	0.007
CRIME DRUGS	-0.004	0.002	-0.008	-0.004	-0.001	-0.004
CRIME HARASS	0.003	0.001	0.001	0.003	0.005	0.003
CRIME OTHER	0	0.001	-0.002	0	0.001	0
CRIME VIOLENT	0.003	0.001	0.002	0.003	0.004	0.003
CRIME THEFT	-0.002	0	-0.003	-0.002	-0.002	-0.002
I(Max MH IO t/MAX MH IO TOTAL)	1.246	0.092	1.064	1.246	1.427	1.246
AV TOTAL INC t-1	0	0	0	0	0	0
AV MH IO t-1	0.02	0.002	0.015	0.02	0.025	0.02
AV MH MISPER ADULT	0.056	0.006	0.045	0.056	0.067	0.056
AV MH MISPER MINOR	0.256	0.04	0.177	0.256	0.335	0.256
AV MH MISPER ADULT t-1	-0.041	0.004	-0.05	-0.041	-0.033	-0.041
AV MH MISPER MINOR t-1	0.157	0.036	0.086	0.157	0.228	0.157
PERRY BARR	0.028	0.005	0.018	0.028	0.037	0.028
ASTON	0.071	0.017	0.037	0.071	0.104	0.071
COVENTRY CENTRAL	0.008	0.015	-0.022	0.008	0.038	0.008
PERRY BARR t-1	-0.002	0.005	-0.012	-0.002	0.008	-0.002
ASTON t-1	0.077	0.019	0.041	0.077	0.114	0.077
COVENTRY CENTRAL t-1	-0.206	0.015	-0.235	-0.206	-0.177	-0.206
SUTTON COLDFIELD	0.105	0.008	0.09	0.105	0.121	0.105
SUTTON COLDFIELD t-1	-0.032	0.007	-0.046	-0.032	-0.019	-0.032
WOLVERHAMPTON CENTRAL	0.017	0.009	-0.002	0.017	0.035	0.017
WOLVERHAMPTON CENTRAL t-1	-0.042	0.009	-0.059	-0.042	-0.026	-0.042
COVID D	-0.24	0.037	-0.312	-0.24	-0.167	-0.24
SD for MH_IO t-1	0.310	0.027	0.262	0.308	0.367	0.305
Ward Model						
Random Effects	Month			Random Walk		
Deviance Information Criterion (DIC)	18769.89					
Watanabe-Akaike information criterion (WAIC)	18875.78					

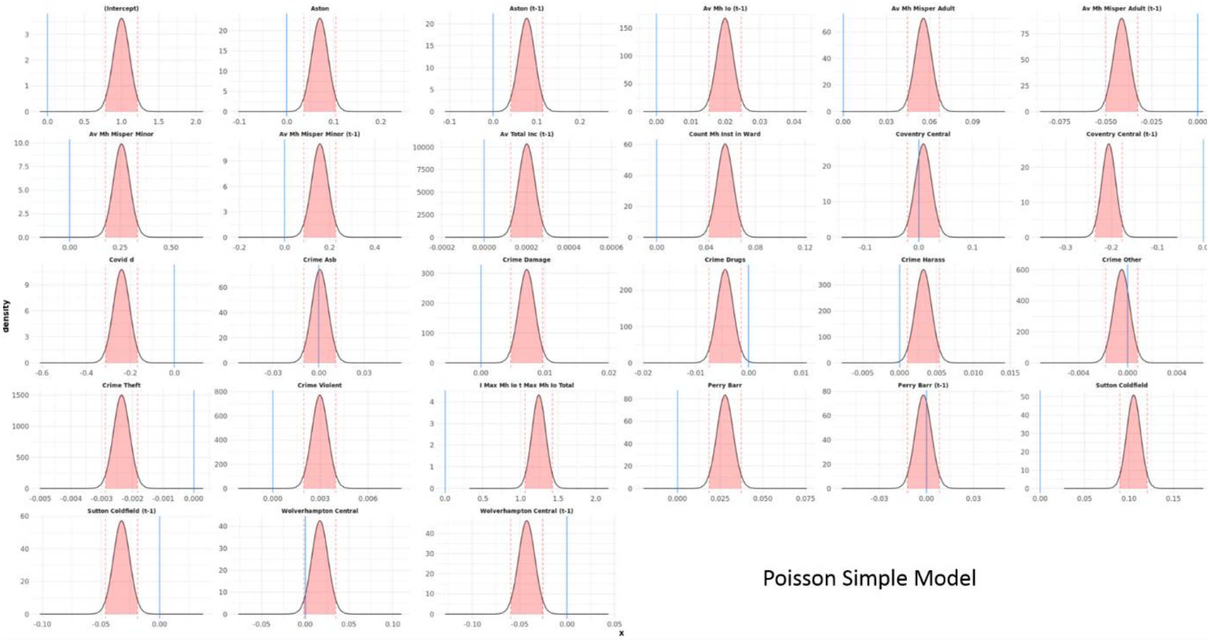


Figure 29 Posterior Densities of Coefficient Estimates

Table 5 Poisson Incidents Only (Besag model)

Besag Model	**Mean**	**SD**	**0.025 Quant**	**Median**	**0.975 Quant**	**Mode**
(Intercept)	1.364	0.373	0.631	1.363	2.106	1.36
COUNT MH INST IN WARD	0.826	0.171	0.497	0.823	1.17	0.818
CRIME ASB	-0.003	0.006	-0.014	-0.003	0.008	-0.003
CRIME DAMAGE	0.003	0.001	0	0.003	0.006	0.003
CRIME DRUGS	0	0.002	-0.003	0	0.004	0
CRIME HARASS	0.001	0.001	-0.001	0.001	0.003	0.001
CRIME OTHER	0	0.001	-0.001	0	0.002	0
CRIME VIOLENT	0.002	0.001	0	0.002	0.003	0.002
CRIME THEFT	0	0	-0.001	0	0.001	0
I(Max MH IO t/MAX MH IO TOTAL)	0.232	0.111	0.013	0.232	0.45	0.232
AV TOTAL INC t-1	0	0	0	0	0.001	0
AV MH IO t-1	0.001	0.002	-0.003	0.001	0.005	0.001
AV MH MISPER ADULT	0.04	0.012	0.017	0.04	0.063	0.04
AV MH MISPER MINOR	0.169	0.165	-0.165	0.169	0.505	0.169
AV MH MISPER ADULT t-1	-0.092	0.017	-0.127	-0.091	-0.058	-0.09
AV MH MISPER MINOR t-1	-0.036	0.129	-0.299	-0.035	0.223	-0.034
PERRY BARR	0.011	0.023	-0.037	0.011	0.058	0.011
ASTON	0.077	0.07	-0.065	0.077	0.22	0.077
COVENTRY CENTRAL	-0.058	0.054	-0.168	-0.058	0.05	-0.057
PERRY BARR t-1	-0.01	0.026	-0.063	-0.01	0.042	-0.01
ASTON t-1	0.083	0.069	-0.058	0.083	0.223	0.083
COVENTRY CENTRAL t-1	-0.161	0.053	-0.268	-0.161	-0.053	-0.16
SUTTON COLDFIELD	0.103	0.035	0.034	0.103	0.174	0.102
SUTTON COLDFIELD t-1	-0.053	0.035	-0.125	-0.053	0.019	-0.053
WOLVERHAMPTON CENTRAL	0.082	0.054	-0.026	0.081	0.195	0.079
WOLVERHAMPTON CENTRAL t-1	-0.015	0.024	-0.064	-0.016	0.034	-0.016
COVID D	-0.052	0.176	-0.405	-0.054	0.31	-0.058
SD for MH_IO t-1	0.0173	0.006	0.0085	0.016399	0.031	0.015
SD for Ward	16.970	1.113	14.909	16.923	19.278	16.818
SD for Monthly Effect	0.108	0.038	0.0543	0.101	0.201	0.090
Ward Model	Besag					
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	17427.21					
Watanabe-Akaike information criterion (WAIC)	17511.40					

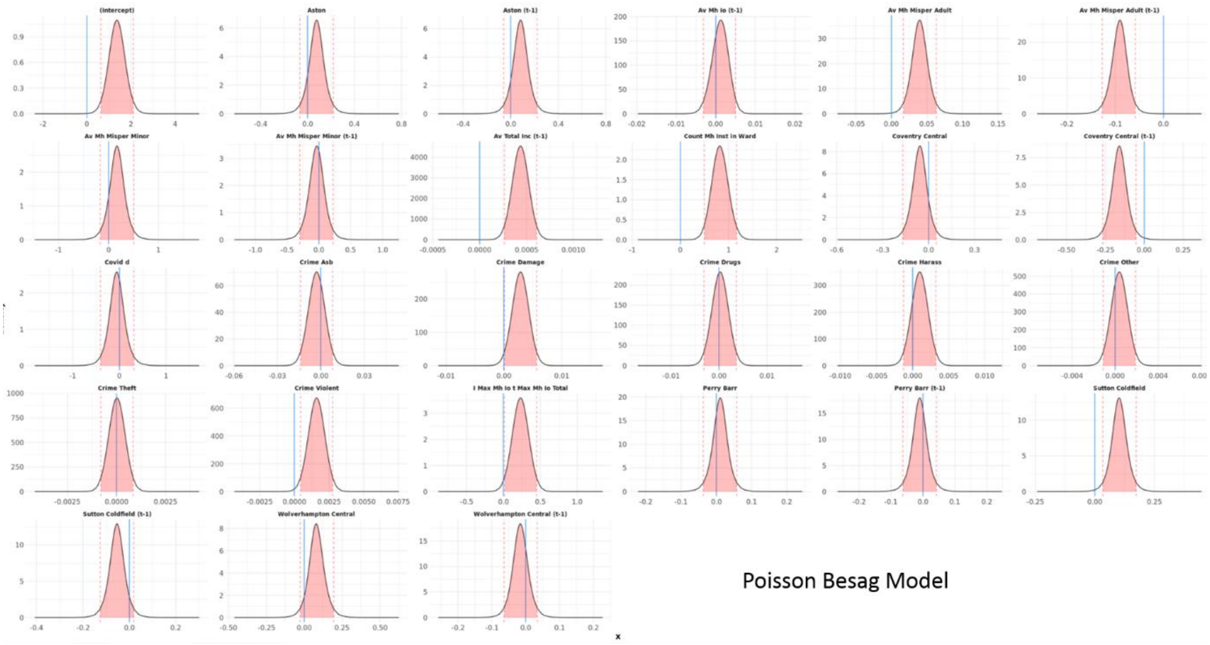


Figure 30 Posterior Densities of Coefficient Estimates

BYM Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	1.353	50.778	-98.341	1.351	100.963	1.353
COUNT MH INST IN WARD	0.795	0.176	0.457	0.792	1.147	0.787
CRIME ASB	-0.003	0.006	-0.014	-0.003	0.008	-0.003
CRIME DAMAGE	0.003	0.001	0	0.003	0.006	0.003
CRIME DRUGS	0	0.002	-0.003	0	0.004	0
CRIME HARASS	0.001	0.001	-0.001	0.001	0.003	0.001
CRIME OTHER	0	0.001	-0.001	0	0.002	0
CRIME VIOLENT	0.002	0.001	0	0.002	0.003	0.002
CRIME THEFT	0	0	-0.001	0	0.001	0
I(Max MH IO t/MAX MH IO TOTAL)	0.23	0.111	0.012	0.23	0.448	0.23
AV TOTAL INC t-1	0	0	0	0	0.001	0
AV MH IO t-1	0.001	0.002	-0.003	0.001	0.005	0.001
AV MH MISPER ADULT	0.032	3.658	-7.15	0.032	7.208	0.032
AV MH MISPER MINOR	0.04	21.894	-42.945	0.04	42.99	0.04
AV MH MISPER ADULT t-1	-0.062	4.023	-7.961	-0.062	7.83	-0.062
AV MH MISPER MINOR t-1	-0.042	18.794	-36.941	-0.043	36.826	-0.042
PERRY BARR	0.058	4.658	-9.086	0.058	9.195	0.058
ASTON	-0.006	14.369	-28.218	-0.007	28.182	-0.006
COVENTRY CENTRAL	0.016	12.442	-24.412	0.016	24.424	0.016
PERRY BARR t-1	0.015	6.189	-12.137	0.015	12.157	0.015
ASTON t-1	0.027	16.599	-32.562	0.026	32.588	0.027
COVENTRY CENTRAL t-1	-0.145	7.681	-15.226	-0.145	14.924	-0.145
SUTTON COLDFIELD	0.121	5.249	-10.185	0.121	10.418	0.121
SUTTON COLDFIELD t-1	-0.065	5.934	-11.716	-0.065	11.577	-0.065
WOLVERHAMPTON CENTRAL	0.057	9.834	-19.251	0.057	19.349	0.057
WOLVERHAMPTON CENTRAL t-1	-0.073	4.673	-9.247	-0.073	9.094	-0.073
COVID D	-0.156	19.091	-37.639	-0.157	37.295	-0.156
Jan	0.016	27.014	-53.021	0.016	53.01	0.016
Feb	0.125	21.5	-42.087	0.125	42.303	0.125
Mar	0.059	15.043	-29.476	0.059	29.569	0.059
May	0.079	20.1	-39.384	0.078	39.509	0.079
Jun	0.235	16.797	-32.743	0.234	33.185	0.235
Jul	-0.024	24.894	-48.9	-0.025	48.81	-0.024
Aug	-0.062	25.983	-51.076	-0.063	50.909	-0.062
Sept	0.214	19.47	-38.012	0.213	38.408	0.214
Oct	-0.071	25.734	-50.595	-0.072	50.411	-0.071
Nov	-0.056	25.119	-49.373	-0.057	49.22	-0.056
Dec	0.072	27.992	-54.886	0.072	54.985	0.072
SD for MH_IO t-1	0.017	0.006	0.008	0.016	0.030	0.014
SD for Ward (iid)	1.594	0.105	1.401	1.589	1.811	1.577
SD for Ward (spatial)	0.025	0.011	0.010	0.022	0.052	0.019
SD for Monthly Effect	0.011	0.006	0.004	0.009	0.0273	0.006
Ward Model	BYM					
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	17427.29					
Watanabe-Akaike information criterion (WAIC)	17511.18					

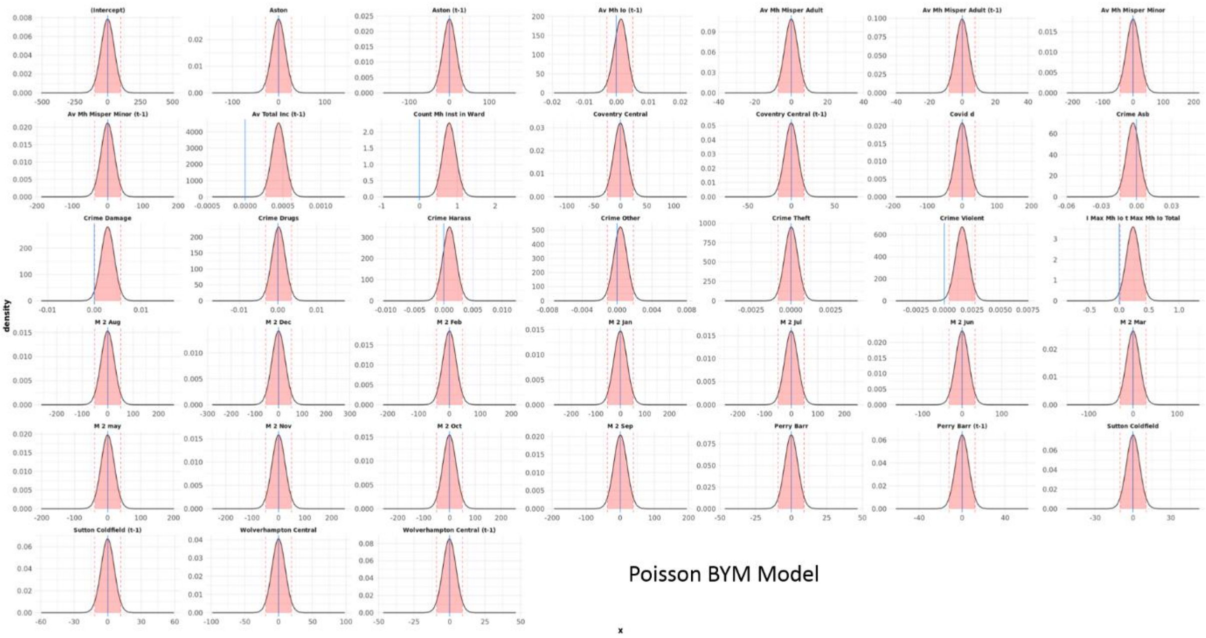


Figure 31 Posterior Densities of Coefficient Estimates

Table 6 Estimates for Zero Inflated Negative Binomial Models

Simple Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	0.944	0.158	0.633	0.945	1.254	0.945
COUNT MH INST IN WARD	0.053	0.01	0.033	0.053	0.073	0.053
CRIME ASB	-0.003	0.008	-0.018	-0.003	0.012	-0.003
CRIME DAMAGE	0.007	0.002	0.003	0.007	0.011	0.007
CRIME DRUGS	-0.005	0.002	-0.01	-0.005	-0.001	-0.005
CRIME HARASS	0.003	0.002	0	0.003	0.007	0.003
CRIME OTHER	0	0.001	-0.002	0	0.002	0
CRIME VIOLENT	0.003	0.001	0.002	0.003	0.005	0.003
CRIME THEFT	-0.003	0	-0.003	-0.003	-0.002	-0.003
I(Max MH IO t/MAX MH IO TOTAL)	-0.113	0.25	-0.605	-0.113	0.377	-0.112
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	0.131	0.042	0.049	0.131	0.213	0.131
AV MH MISPER ADULT	-0.022	0.042	-0.105	-0.022	0.06	-0.022
AV MH MISPER MINOR	0.536	0.278	-0.003	0.534	1.088	0.529
AV MH MISPER ADULT t-1	-0.095	0.031	-0.156	-0.095	-0.034	-0.094
AV MH MISPER MINOR t-1	-0.761	0.265	-1.287	-0.76	-0.247	-0.756
PERRY BARR	0.104	0.03	0.045	0.104	0.163	0.103
ASTON	0.123	0.102	-0.077	0.123	0.324	0.123
COVENTRY CENTRAL	-0.327	0.123	-0.569	-0.327	-0.087	-0.326
PERRY BARR t-1	-0.038	0.031	-0.098	-0.038	0.022	-0.039
ASTON t-1	0.316	0.106	0.109	0.316	0.525	0.315
COVENTRY CENTRAL t-1	0.125	0.125	-0.126	0.127	0.364	0.131
SUTTON COLDFIELD	-0.045	0.06	-0.163	-0.045	0.074	-0.045
SUTTON COLDFIELD t-1	0.014	0.038	-0.061	0.014	0.088	0.014
WOLVERHAMPTON CENTRAL	-0.011	0.053	-0.116	-0.011	0.094	-0.011
WOLVERHAMPTON CENTRAL t-1	0.156	0.058	0.043	0.156	0.272	0.155
COVID D	-1.076	0.257	-1.587	-1.074	-0.578	-1.069
Size for Nbinomial Zero Inflated Obs	17.673	1.234	15.407	17.615	20.229	17.491
Zero-probability Parameter	0.161	0.006	0.149	0.161	0.173	0.161
SD for MH_IO t-1	0.069	0.011	0.050	0.068	0.093	0.066
Ward Model						
Random Effects	Month			Random Walk		
Deviance Information Criterion (DIC)	20636.95					
Watanabe-Akaike information criterion (WAIC)	20638.29					

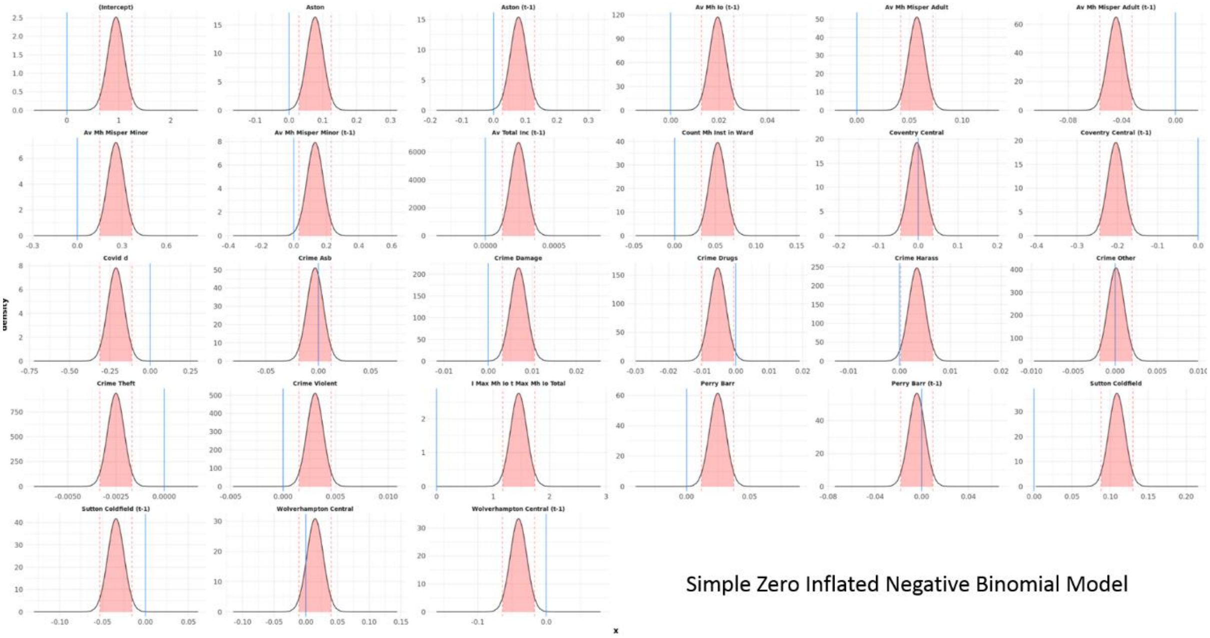


Figure 32 Posterior Densities for Estimated Coefficients Incidents

Besag Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	1.661	0.244	1.189	1.658	2.153	1.651
COUNT MH INST IN WARD	0.106	0.036	0.035	0.106	0.178	0.105
CRIME ASB	-0.003	0.007	-0.017	-0.003	0.012	-0.003
CRIME DAMAGE	0.005	0.002	0.001	0.005	0.008	0.005
CRIME DRUGS	-0.002	0.002	-0.006	-0.002	0.003	-0.002
CRIME HARASS	0.003	0.002	0	0.003	0.006	0.003
CRIME OTHER	0.001	0.001	-0.001	0.001	0.003	0.001
CRIME VIOLENT	0.003	0.001	0.001	0.003	0.004	0.003
CRIME THEFT	-0.001	0.001	-0.002	-0.001	0	-0.001
I(Max MH IO t/MAX MH IO TOTAL)	0.784	0.148	0.495	0.784	1.075	0.783
AV TOTAL INC t-1	0.001	0	0.001	0.001	0.001	0.001
AV MH IO t-1	0.007	0.003	0.001	0.007	0.012	0.006
AV MH MISPER ADULT	0.051	0.01	0.031	0.051	0.072	0.051
AV MH MISPER MINOR	0.253	0.125	0.006	0.252	0.505	0.251
AV MH MISPER ADULT t-1	-0.08	0.014	-0.109	-0.079	-0.054	-0.078
AV MH MISPER MINOR t-1	0.029	0.104	-0.181	0.029	0.233	0.031
PERRY BARR	0.013	0.017	-0.022	0.014	0.048	0.014
ASTON	0.085	0.053	-0.021	0.085	0.191	0.085
COVENTRY CENTRAL	-0.057	0.041	-0.141	-0.056	0.024	-0.055
PERRY BARR t-1	-0.012	0.019	-0.051	-0.012	0.026	-0.012
ASTON t-1	0.091	0.053	-0.015	0.092	0.196	0.092
COVENTRY CENTRAL t-1	-0.195	0.041	-0.277	-0.195	-0.114	-0.194
SUTTON COLDFIELD	0.111	0.027	0.058	0.11	0.166	0.109
SUTTON COLDFIELD t-1	-0.046	0.027	-0.1	-0.046	0.008	-0.046
WOLVERHAMPTON CENTRAL	0.06	0.041	-0.019	0.059	0.146	0.057
WOLVERHAMPTON CENTRAL t-1	-0.025	0.02	-0.064	-0.025	0.016	-0.025
COVID D	-0.122	0.136	-0.385	-0.124	0.156	-0.129
Size for Nbinomial Zero Inflated Obs	31.550	3.117	25.824	31.409	38.025	31.188
Zero-probability Parameter	0.155	0.005	0.146	0.154	0.165	0.153
SD for MH_IO t-1	0.027	0.007	0.016	0.026	0.044	0.024
SD for Ward	3.218	0.309	2.618	3.219	3.828	3.240
SD for Month	0.080	0.033	0.036	0.073	0.165	0.061
Ward Model	Ward			Besag		
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	20186.62					
Watanabe-Akaike information criterion (WAIC)	20203.04					

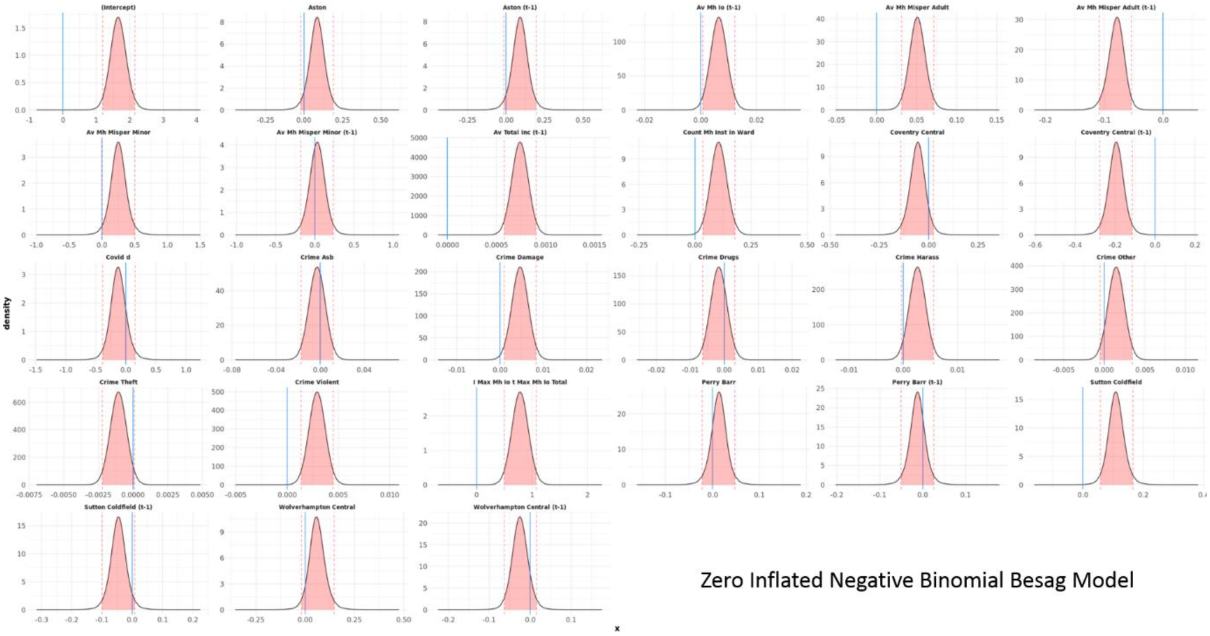


Figure 33 Posterior Densities for Estimated Coefficients Incidents

BYM Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	1.491	50.735	-98.119	1.489	101.017	1.491
COUNT MH INST IN WARD	0.103	0.037	0.031	0.103	0.177	0.102
CRIME ASB	-0.003	0.007	-0.017	-0.003	0.012	-0.003
CRIME DAMAGE	0.005	0.002	0.001	0.005	0.008	0.005
CRIME DRUGS	-0.002	0.002	-0.007	-0.002	0.003	-0.002
CRIME HARASS	0.003	0.002	0	0.003	0.006	0.003
CRIME OTHER	0.001	0.001	-0.001	0.001	0.003	0.001
CRIME VIOLENT	0.003	0.001	0.001	0.003	0.005	0.003
CRIME THEFT	-0.001	0.001	-0.002	-0.001	0	-0.001
I(Max MH IO t/MAX MH IO TOTAL)	0.797	0.148	0.507	0.797	1.089	0.796
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	-0.003	0.054	-0.106	-0.005	0.107	-0.009
AV MH MISPER ADULT	-0.013	3.659	-7.197	-0.013	7.166	-0.013
AV MH MISPER MINOR	0.003	21.895	-42.984	0.003	42.955	0.003
AV MH MISPER ADULT t-1	-0.098	4.022	-7.995	-0.098	7.792	-0.098
AV MH MISPER MINOR t-1	-0.628	18.793	-37.525	-0.629	36.237	-0.628
PERRY BARR	0.118	4.658	-9.027	0.118	9.256	0.118
ASTON	-0.112	14.369	-28.323	-0.113	28.075	-0.112
COVENTRY CENTRAL	-0.153	12.445	-24.588	-0.154	24.261	-0.153
PERRY BARR t-1	-0.026	6.191	-12.181	-0.026	12.118	-0.026
ASTON t-1	0.123	16.598	-32.465	0.123	32.684	0.123
COVENTRY CENTRAL t-1	-0.065	7.682	-15.148	-0.066	15.005	-0.065
SUTTON COLDFIELD	0.075	5.25	-10.232	0.075	10.373	0.075
SUTTON COLDFIELD t-1	-0.044	5.935	-11.695	-0.044	11.598	-0.044
WOLVERHAMPTON CENTRAL	0.152	9.836	-19.158	0.152	19.447	0.152
WOLVERHAMPTON CENTRAL t-1	0.04	4.673	-9.134	0.04	9.207	0.04
COVID D	-0.879	19.093	-38.364	-0.879	36.575	-0.879
Jan	0.101	27.012	-52.932	0.1	53.09	0.101
Feb	0.465	21.501	-41.75	0.464	42.644	0.465
Mar	-0.108	15.039	-29.635	-0.108	29.395	-0.108
May	0.158	20.104	-39.313	0.157	39.595	0.158
Jun	0.306	16.798	-32.673	0.306	33.258	0.306
Jul	-0.042	24.895	-48.919	-0.043	48.795	-0.042
Aug	-0.171	25.984	-51.186	-0.172	50.801	-0.171
Sept	0.298	19.472	-37.932	0.297	38.496	0.298
Oct	-0.085	25.735	-50.613	-0.086	50.399	-0.085
Nov	-0.021	25.118	-49.337	-0.022	49.254	-0.021
Dec	0.417	27.994	-54.544	0.416	55.333	0.417
Size for Nbinomial Zero Inflated Obs	31.022	3.032	25.597	30.823	37.465	30.424
Zero-probability Parameter	0.161	0.006	0.149	0.161	0.173	0.161
SD for MH_IO t-1	0.027	0.007	0.016	0.026	0.042	0.024
SD for Ward (idd component)	0.302	0.028	0.252	0.301	0.363	0.296
SD for Ward (spatial component)	0.033	0.020	0.012	0.027	0.088	0.020
SD for Month	0.011	0.006	0.004	0.009	0.028	0.006
Ward Model	Ward			BYM		
Random Effects	Month & Lagged MH IO			Random Walk		

Deviance Information Criterion (DIC)	20193.55
Watanabe-Akaike information criterion (WAIC)	20208.49

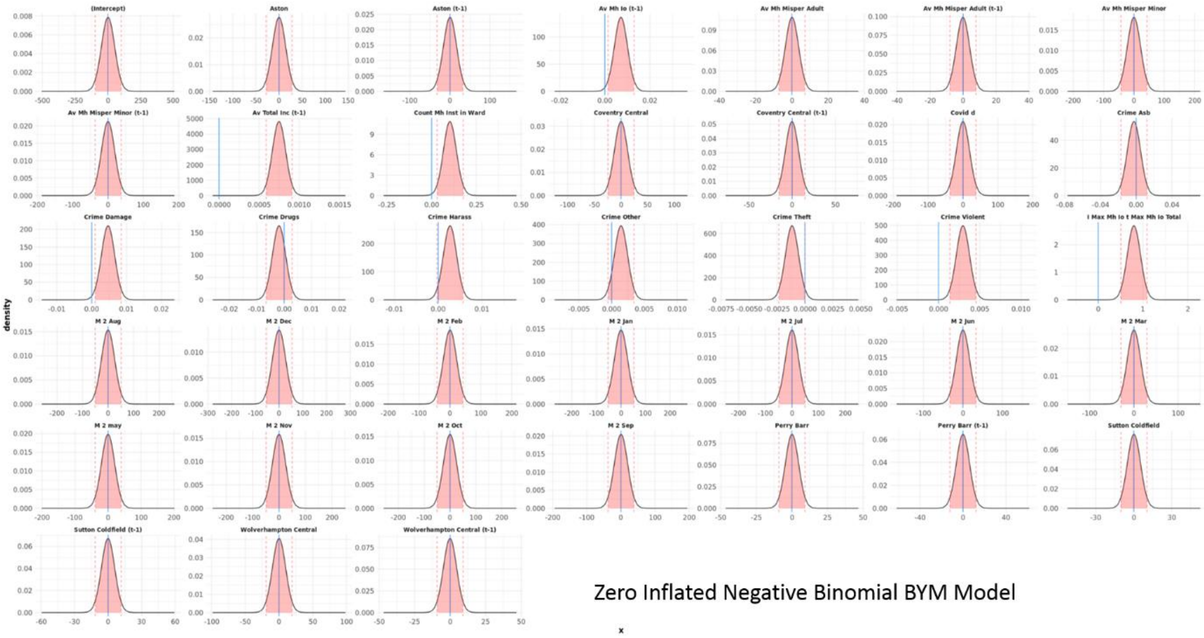
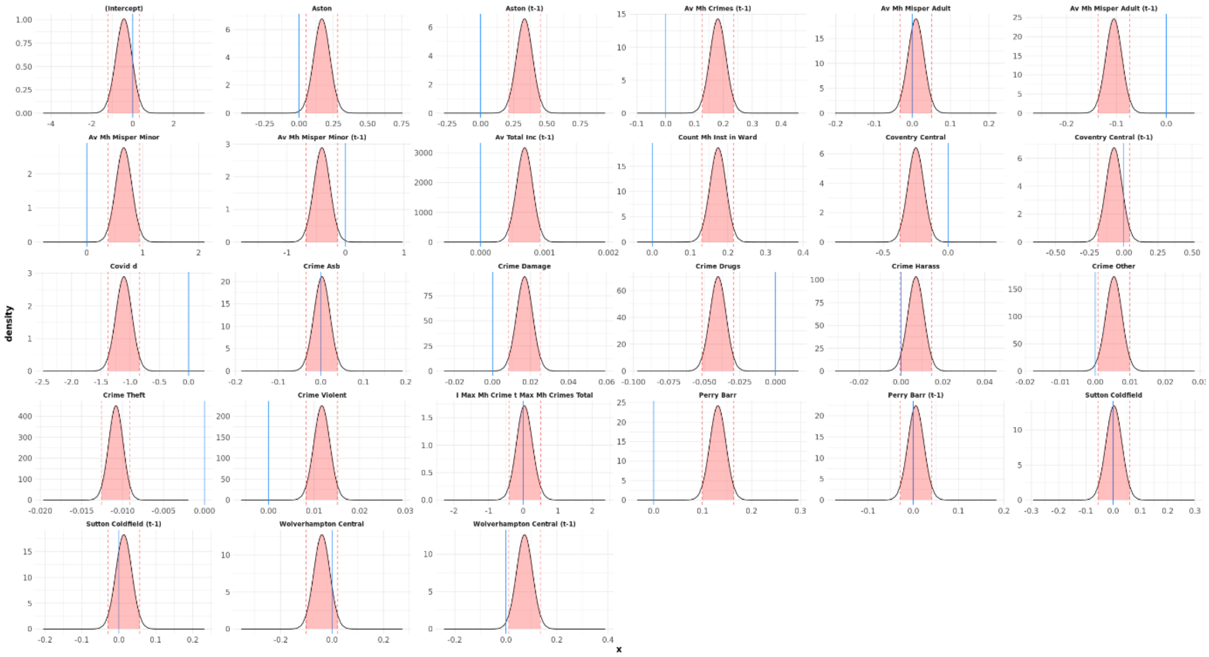


Figure 34 Posterior Densities for Estimated Coefficients Incidents

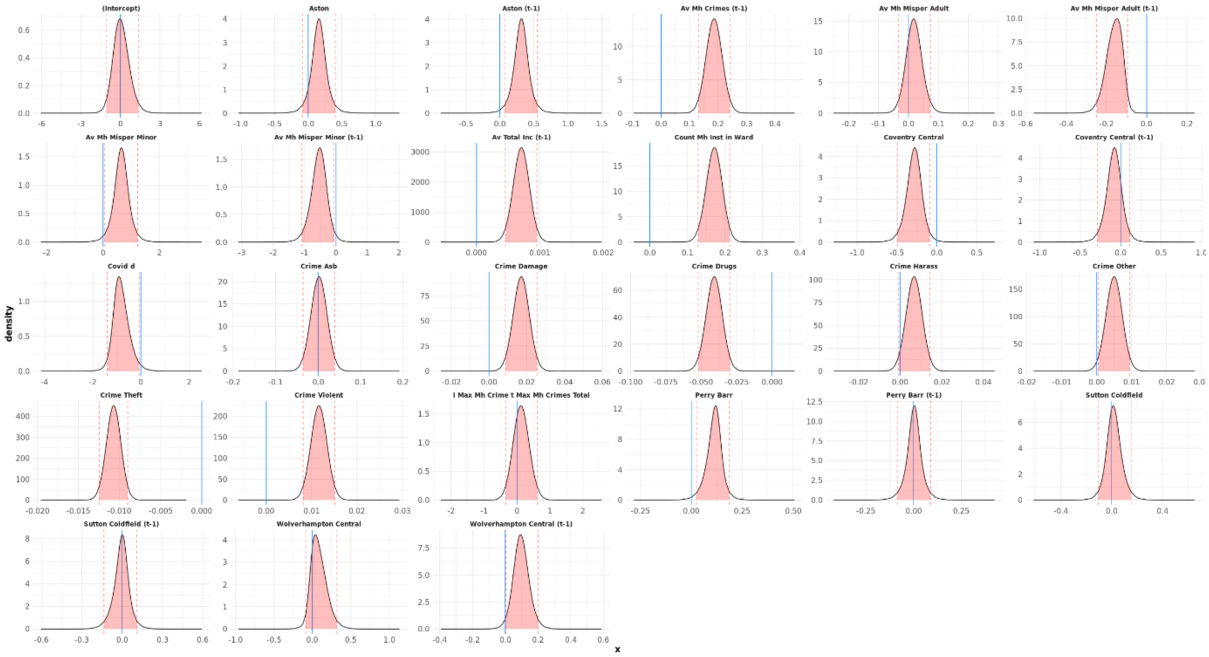
Estimate of Coefficients Crime Models

Table 7 Mental Health Associated with Crimes Poisson Models

Simple Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	-0.437	0.395	-1.22	-0.435	0.33	-0.429
COUNT MH INST IN WARD	0.174	0.021	0.131	0.174	0.215	0.174
CRIME ASB	0.003	0.019	-0.035	0.003	0.04	0.003
CRIME DAMAGE	0.017	0.004	0.009	0.017	0.025	0.017
CRIME DRUGS	-0.04	0.006	-0.052	-0.04	-0.029	-0.04
CRIME HARASS	0.007	0.004	-0.001	0.007	0.015	0.007
CRIME OTHER	0.005	0.002	0.001	0.005	0.01	0.005
CRIME VIOLENT	0.012	0.002	0.008	0.012	0.015	0.012
CRIME THEFT	-0.011	0.001	-0.013	-0.011	-0.009	-0.011
I(Max MH IO t/MAX MH IO TOTAL)	0.042	0.233	-0.408	0.04	0.507	0.034
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	0.181	0.028	0.127	0.181	0.236	0.181
AV MH MISPER ADULT	0.009	0.021	-0.032	0.009	0.051	0.009
AV MH MISPER MINOR	0.663	0.144	0.38	0.662	0.947	0.662
AV MH MISPER ADULT t-1	-0.105	0.016	-0.137	-0.105	-0.074	-0.105
AV MH MISPER MINOR t-1	-0.405	0.138	-0.677	-0.404	-0.135	-0.404
PERRY BARR	0.131	0.016	0.099	0.131	0.163	0.131
ASTON	0.168	0.059	0.052	0.168	0.283	0.168
COVENTRY CENTRAL	-0.249	0.062	-0.371	-0.249	-0.127	-0.249
PERRY BARR t-1	0.006	0.018	-0.029	0.006	0.041	0.006
ASTON t-1	0.332	0.061	0.213	0.332	0.451	0.332
COVENTRY CENTRAL t-1	-0.073	0.059	-0.19	-0.072	0.042	-0.071
SUTTON COLDFIELD	0.003	0.03	-0.056	0.003	0.061	0.003
SUTTON COLDFIELD t-1	0.014	0.022	-0.029	0.014	0.056	0.014
WOLVERHAMPTON CENTRAL	-0.04	0.031	-0.101	-0.04	0.022	-0.039
WOLVERHAMPTON CENTRAL t-1	0.073	0.032	0.011	0.073	0.136	0.073
COVID D	-1.107	0.138	-1.379	-1.107	-0.838	-1.106
SD for MH_IO t-1	0.142	0.050	0.066	0.135	0.263	0.121
Ward Model						
Random Effects	Month			Random Walk		
Deviance Information Criterion (DIC)	8424.9					
Watanabe-Akaike information criterion (WAIC)	8447.0					


(Intercept)
Aston
Aston (t-1)
Av Mh Crimes (t-1)
Av Mh Misper Adult
Av Mh Misper Adult (t-1)
Av Mh Misper Minor
Av Mh Misper Minor (t-1)
Av Total Inc (t-1)
Count Mh Inst in Ward
Coventry Central
Coventry Central (t-1)
Covid d
Crime Asb
Crime Damage
Crime Drugs
Crime Harass
Crime Other
Crime Theft
Crime Violent
I Max Mh Crime t Max Mh Crimes Total
Perry Barr
Perry Barr (t-1)
Sutton Coldfield
Sutton Coldfield (t-1)
Wolverhampton Central
Wolverhampton Central (t-1)
density
x

Besag Model	**Mean**	**SD**	**0.025 Quant**	**Median**	**0.975 Quant**	**Mode**
(Intercept)	0.069	0.612	-1.049	0.037	1.363	-0.03
COUNT MH INST IN WARD	0.171	0.021	0.129	0.172	0.213	0.172
CRIME ASB	0.002	0.019	-0.035	0.002	0.039	0.002
CRIME DAMAGE	0.017	0.004	0.009	0.017	0.025	0.017
CRIME DRUGS	-0.041	0.006	-0.052	-0.041	-0.03	-0.041
CRIME HARASS	0.007	0.004	-0.001	0.007	0.014	0.007
CRIME OTHER	0.005	0.002	0	0.005	0.009	0.005
CRIME VIOLENT	0.012	0.002	0.008	0.012	0.015	0.012
CRIME THEFT	-0.011	0.001	-0.012	-0.011	-0.009	-0.011
I(Max MH IO t/MAX MH IO TOTAL)	0.129	0.244	-0.34	0.126	0.617	0.118
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	0.186	0.028	0.131	0.186	0.242	0.186
AV MH MISPER ADULT	0.019	0.027	-0.033	0.018	0.073	0.017
AV MH MISPER MINOR	0.647	0.286	0.058	0.649	1.226	0.652
AV MH MISPER ADULT t-1	-0.162	0.04	-0.248	-0.158	-0.095	-0.148
AV MH MISPER MINOR t-1	-0.546	0.256	-1.083	-0.536	-0.062	-0.517
PERRY BARR	0.112	0.04	0.025	0.115	0.186	0.119
ASTON	0.159	0.119	-0.085	0.16	0.403	0.16
COVENTRY CENTRAL	-0.284	0.101	-0.495	-0.281	-0.089	-0.276
PERRY BARR t-1	0.003	0.042	-0.086	0.003	0.089	0.004
ASTON t-1	0.315	0.118	0.071	0.317	0.554	0.319
COVENTRY CENTRAL t-1	-0.083	0.1	-0.287	-0.081	0.113	-0.078
SUTTON COLDFIELD	0.019	0.063	-0.104	0.017	0.154	0.013
SUTTON COLDFIELD t-1	-0.006	0.06	-0.135	-0.003	0.111	0.002
WOLVERHAMPTON CENTRAL	0.085	0.104	-0.086	0.073	0.32	0.04
WOLVERHAMPTON CENTRAL t-1	0.098	0.049	0.004	0.096	0.199	0.094
COVID D	-0.812	0.334	-1.399	-0.842	-0.075	-0.905
SD for MH_IO t-1	0.151374	0.051569	0.074473	0.143158	0.274992	0.12809
SD for Ward	0.010618	0.006473	0.003878	0.008749	0.028093	0.006373
SD for Monthly Effect	0.14576	0.084887	0.036378	0.127873	0.359691	0.09092
Ward Model	Besag					
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	8412.53					
Watanabe-Akaike information criterion (WAIC)	8435.67					


(Intercept)
Aston
Aston (t-1)
Av Mh Crimes (t-1)
Av Mh Misper Adult
Av Mh Misper Adult (t-1)
Av Mh Misper Minor
Av Mh Misper Minor (t-1)
Av Total Inc (t-1)
Count Mh Inst in Ward
Coventry Central
Coventry Central (t-1)
Covid d
Crime Asb
Crime Damage
Crime Drugs
Crime Harass
Crime Other
Crime Theft
Crime Violent
I Max Mh Crime t Max Mh Crimes Total
Perry Barr
Perry Barr (t-1)
Sutton Coldfield
Sutton Coldfield (t-1)
Wolverhampton Central
Wolverhampton Central (t-1)
density
x

BYM Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	-0.875	50.779	-100.571	-0.876	98.738	-0.875
COUNT MH INST IN WARD	0.309	0.083	0.148	0.308	0.474	0.307
CRIME ASB	0.018	0.021	-0.023	0.018	0.058	0.018
CRIME DAMAGE	0.011	0.005	0.001	0.011	0.021	0.011
CRIME DRUGS	-0.01	0.007	-0.023	-0.01	0.003	-0.01
CRIME HARASS	0.009	0.004	0.001	0.009	0.017	0.009
CRIME OTHER	0.005	0.003	-0.001	0.005	0.01	0.005
CRIME VIOLENT	0.014	0.002	0.009	0.014	0.018	0.014
CRIME THEFT	-0.009	0.002	-0.012	-0.009	-0.006	-0.009
I(Max MH IO t/MAX MH IO TOTAL)	0.495	0.157	0.187	0.495	0.803	0.495
AV TOTAL INC t-1	0.001	0	0.001	0.001	0.002	0.001
AV MH IO t-1	-0.133	0.032	-0.195	-0.133	-0.071	-0.132
AV MH MISPER ADULT	0.029	3.658	-7.153	0.029	7.205	0.029
AV MH MISPER MINOR	0.127	21.895	-42.86	0.126	43.077	0.127
AV MH MISPER ADULT t-1	-0.09	4.024	-7.99	-0.09	7.804	-0.09
AV MH MISPER MINOR t-1	-0.603	18.794	-37.502	-0.603	36.266	-0.603
PERRY BARR	0.152	4.658	-8.992	0.152	9.29	0.152
ASTON	-0.146	14.37	-28.36	-0.147	28.044	-0.146
COVENTRY CENTRAL	-0.164	12.443	-24.593	-0.165	24.244	-0.164
PERRY BARR t-1	0.008	6.19	-12.145	0.008	12.151	0.008
ASTON t-1	0.101	16.6	-32.49	0.1	32.664	0.101
COVENTRY CENTRAL t-1	-0.202	7.682	-15.284	-0.203	14.867	-0.202
SUTTON COLDFIELD	0.098	5.249	-10.208	0.098	10.396	0.098
SUTTON COLDFIELD t-1	-0.025	5.935	-11.676	-0.025	11.617	-0.025
WOLVERHAMPTON CENTRAL	0.119	9.834	-19.189	0.119	19.412	0.119
WOLVERHAMPTON CENTRAL t-1	0.035	4.673	-9.14	0.035	9.203	0.035
COVID D	-0.774	19.092	-38.258	-0.774	36.679	-0.774
Jan	-0.002	27.014	-53.039	-0.003	52.991	-0.002
Feb	0.323	21.503	-41.894	0.322	42.505	0.323
Mar	0.19	15.045	-29.348	0.189	29.703	0.19
May	0.266	20.1	-39.197	0.265	39.696	0.266
Jun	0.344	16.797	-32.635	0.343	33.295	0.344
Jul	-0.084	24.894	-48.96	-0.085	48.751	-0.084
Aug	-0.198	25.984	-51.214	-0.199	50.776	-0.198
Sept	0.18	19.471	-38.048	0.179	38.376	0.18
Oct	-0.086	25.733	-50.609	-0.087	50.395	-0.086
Nov	0.003	25.12	-49.316	0.002	49.28	0.003
Dec	0.36	27.992	-54.598	0.359	55.272	0.36
SD for MH_IO t-1	0.010878	0.006914	0.003767	0.008869	0.029567	0.006375
SD for Ward (iid)	0.670965	0.057571	0.566598	0.667706	0.792487	0.66089
SD for Ward (spatial)	0.026694	0.013289	0.010435	0.023464	0.061295	0.01862
SD for Monthly Effect	0.009826	0.005612	0.003719	0.008261	0.02486	0.006172
Ward Model	BYM					
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	7905.13					
Watanabe-Akaike information criterion (WAIC)	7949.38					

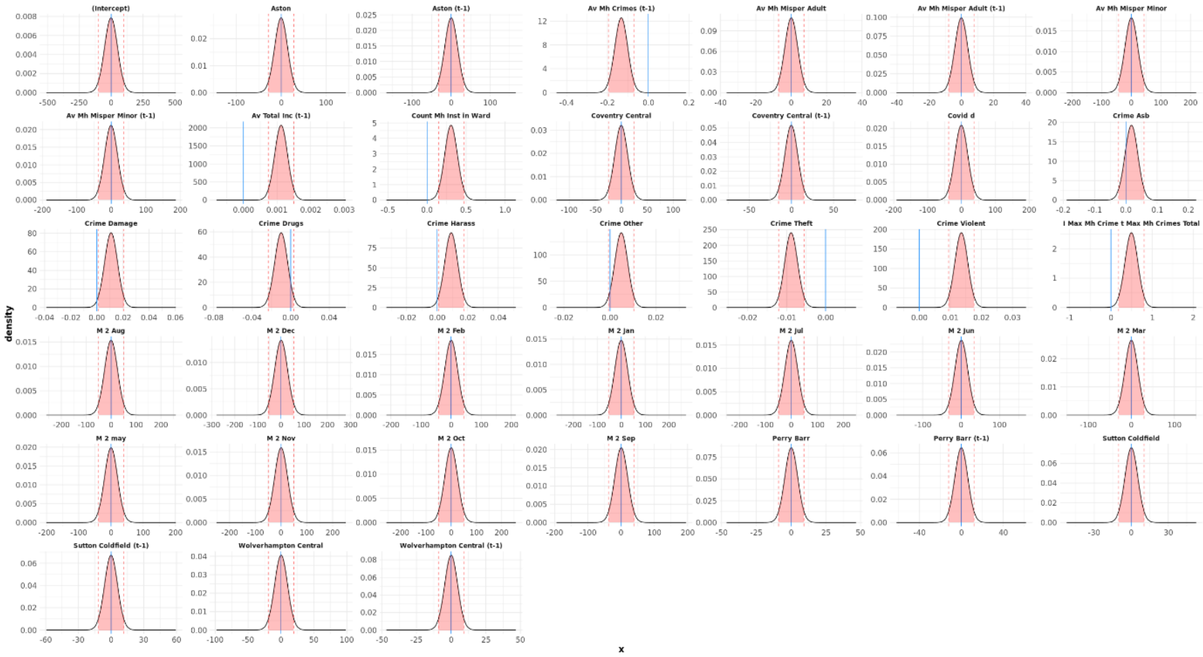
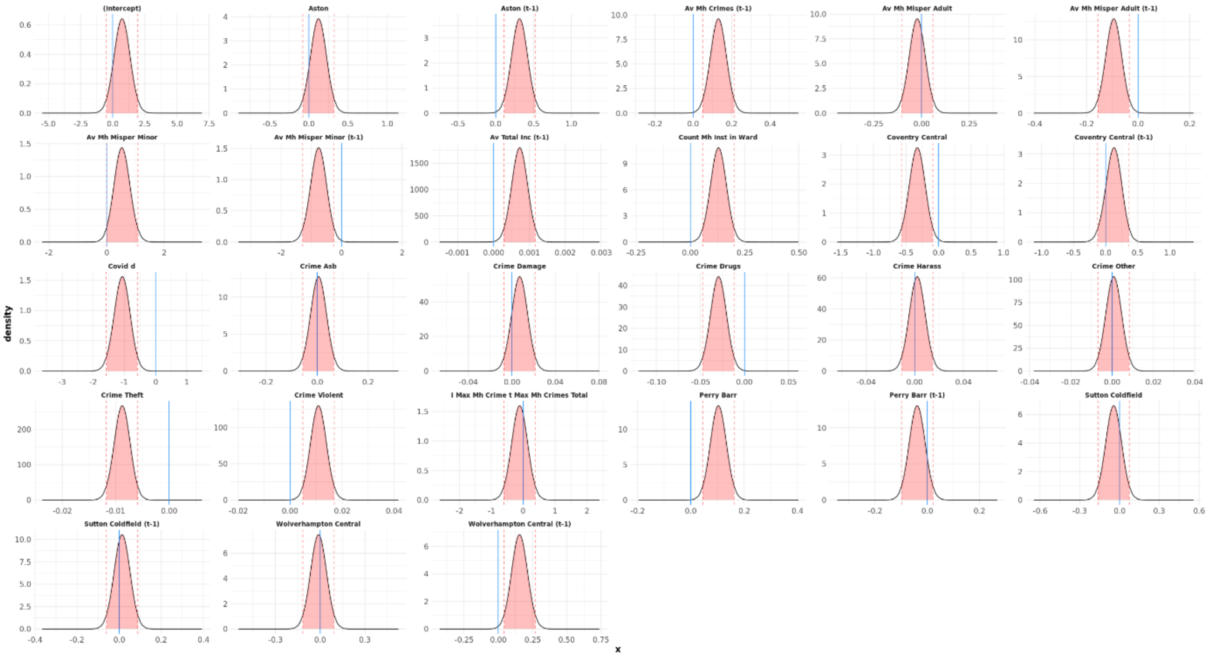
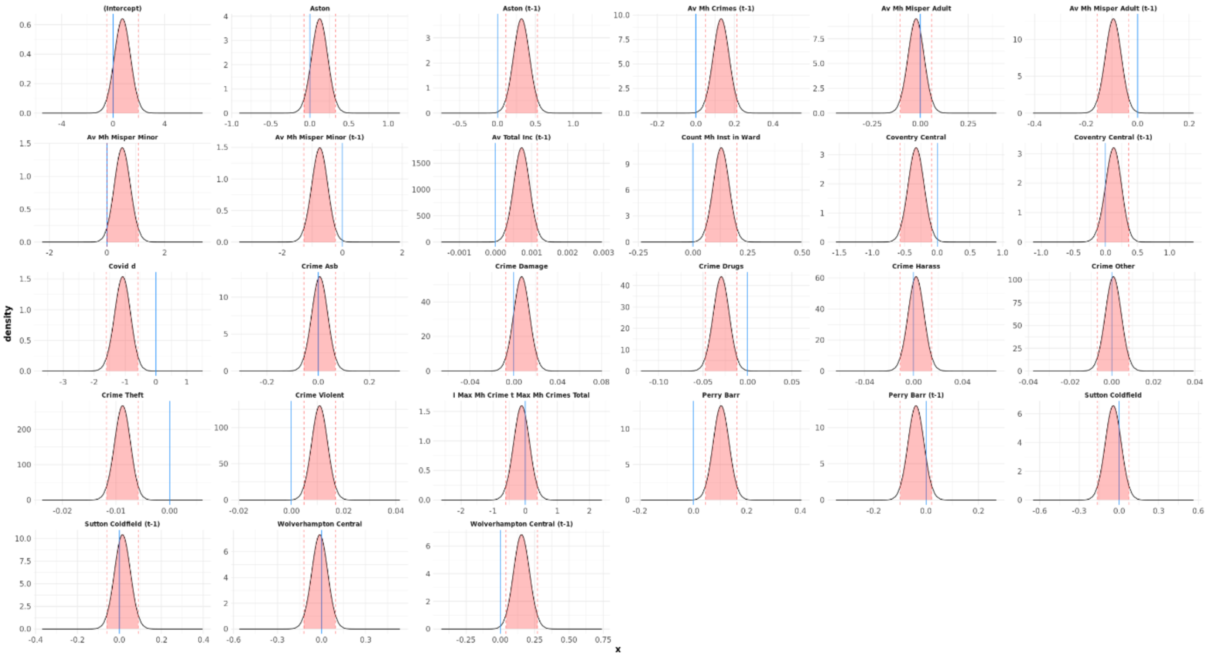

(Intercept)
Aston
Aston (t-1)
Av Mh Crimes (t-1)
Av Mh Misper Adult
Av Mh Misper Adult (t-1)
Av Mh Misper Minor
Av Mh Misper Minor (t-1)
Av Total Inc (t-1)
Count Mh Inst in Ward
Coventry Central
Coventry Central (t-1)
Covid d
Crime Asb
Crime Damage
Crime Drugs
Crime Harass
Crime Other
Crime Theft
Crime Violent
l Max Mh Crime t Max Mh Crimes Total
M 2 Aug
M 2 Dec
M 2 Feb
M 2 Jan
M 2 Jul
M 2 Jun
M 2 Mar
M 2 may
M 2 Nov
M 2 Oct
M 2 Sep
Perry Barr
Perry Barr (t-1)
Sutton Coldfield
Sutton Coldfield (t-1)
Wolverhampton Central
Wolverhampton Central (t-1)
density
x

Table 8 Estimates for Mental Health Associated Crimes Zero Inflated Negative Binomial Models

Simple Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	0.731	0.622	-0.491	0.731	1.95	0.732
COUNT MH INST IN WARD	0.129	0.037	0.057	0.13	0.202	0.13
CRIME ASB	0.005	0.031	-0.056	0.005	0.067	0.006
CRIME DAMAGE	0.007	0.007	-0.007	0.007	0.022	0.007
CRIME DRUGS	-0.03	0.009	-0.047	-0.03	-0.012	-0.029
CRIME HARASS	0.002	0.007	-0.011	0.002	0.015	0.002
CRIME OTHER	0.001	0.004	-0.007	0.001	0.008	0.001
CRIME VIOLENT	0.011	0.003	0.005	0.011	0.017	0.011
CRIME THEFT	-0.009	0.001	-0.012	-0.009	-0.006	-0.009
I(Max MH IO t/MAX MH IO TOTAL)	-0.113	0.25	-0.605	-0.113	0.377	-0.112
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	0.131	0.042	0.049	0.131	0.213	0.131
AV MH MISPER ADULT	-0.022	0.042	-0.105	-0.022	0.06	-0.022
AV MH MISPER MINOR	0.536	0.278	-0.003	0.534	1.088	0.529
AV MH MISPER ADULT t-1	-0.095	0.031	-0.156	-0.095	-0.034	-0.094
AV MH MISPER MINOR t-1	-0.761	0.265	-1.287	-0.76	-0.247	-0.756
PERRY BARR	0.104	0.03	0.045	0.104	0.163	0.103
ASTON	0.123	0.102	-0.077	0.123	0.324	0.123
COVENTRY CENTRAL	-0.327	0.123	-0.569	-0.327	-0.087	-0.326
PERRY BARR t-1	-0.038	0.031	-0.098	-0.038	0.022	-0.039
ASTON t-1	0.316	0.106	0.109	0.316	0.525	0.315
COVENTRY CENTRAL t-1	0.125	0.125	-0.126	0.127	0.364	0.131
SUTTON COLDFIELD	-0.045	0.06	-0.163	-0.045	0.074	-0.045
SUTTON COLDFIELD t-1	0.014	0.038	-0.061	0.014	0.088	0.014
WOLVERHAMPTON CENTRAL	-0.011	0.053	-0.116	-0.011	0.094	-0.011
WOLVERHAMPTON CENTRAL t-1	0.156	0.058	0.043	0.156	0.272	0.155
COVID D	-1.076	0.257	-1.587	-1.074	-0.578	-1.069
Size for Nbinomial Zero Inflated Obs	3.116963	0.623899	2.058504369	3.059092	4.4929205	2.952358
Zero-probability Parameter	0.571381	0.008107	0.55538853	0.57139	0.5871572	0.571486
SD for MH_IO t-1	0.01053	0.00642	0.003863549	0.008673	0.027871	0.006283
Ward Model	None					
Random Effects	Month			Random Walk		
Deviance Information Criterion (DIC)	9204.68					
Watanabe-Akaike information criterion (WAIC)	9204.61					

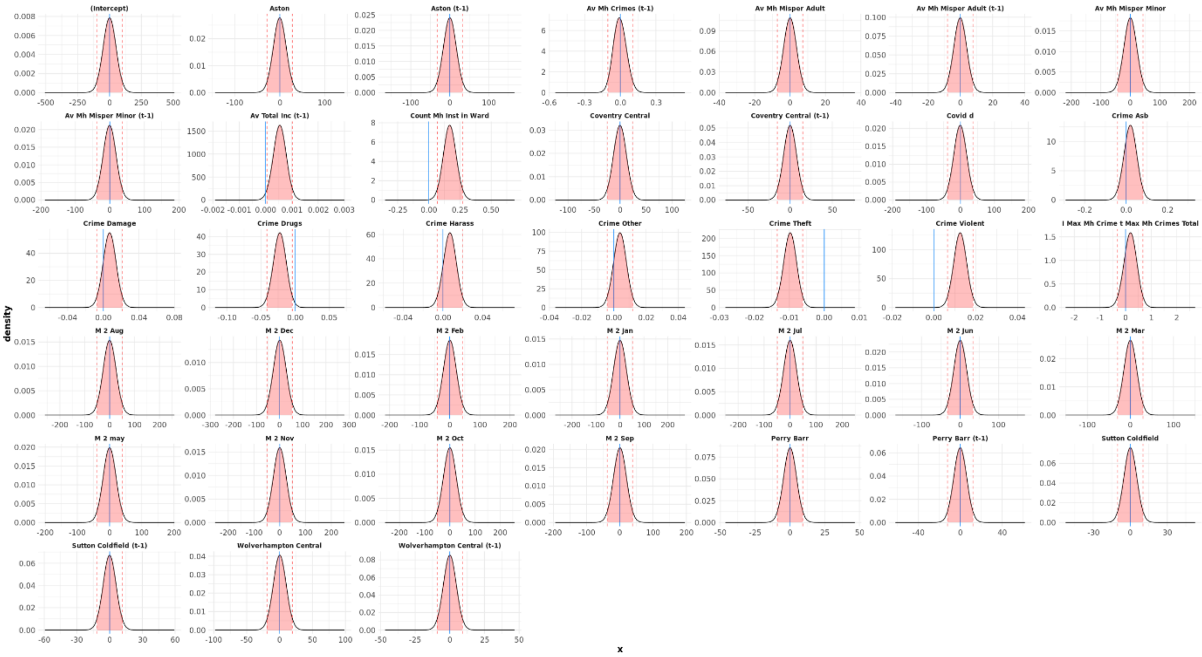

(Intercept)
Aston
Aston (t-1)
Av Mh Crimes (t-1)
Av Mh Misper Adult
Av Mh Misper Adult (t-1)
Av Mh Misper Minor
Av Mh Misper Minor (t-1)
Av Total Inc (t-1)
Count Mh Inst in Ward
Coventry Central
Coventry Central (t-1)
Covid d
Crime Asb
Crime Damage
Crime Drugs
Crime Harass
Crime Other
Crime Theft
Crime Violent
I Max Mh Crime t Max Mh Crimes Total
Perry Barr
Perry Barr (t-1)
Sutton Coldfield
Sutton Coldfield (t-1)
Wolverhampton Central
Wolverhampton Central (t-1)
density
x

Besag Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	0.725	0.624	-0.502	0.725	1.949	0.726
COUNT MH INST IN WARD	0.129	0.037	0.057	0.13	0.202	0.13
CRIME ASB	0.005	0.031	-0.056	0.006	0.067	0.006
CRIME DAMAGE	0.007	0.007	-0.007	0.007	0.022	0.007
CRIME DRUGS	-0.03	0.009	-0.047	-0.03	-0.012	-0.029
CRIME HARASS	0.002	0.007	-0.011	0.002	0.015	0.002
CRIME OTHER	0.001	0.004	-0.007	0.001	0.008	0.001
CRIME VIOLENT	0.011	0.003	0.005	0.011	0.017	0.011
CRIME THEFT	-0.009	0.001	-0.012	-0.009	-0.006	-0.009
I(Max MH IO t/MAX MH IO TOTAL)	-0.113	0.25	-0.605	-0.113	0.378	-0.113
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	0.131	0.042	0.05	0.131	0.213	0.131
AV MH MISPER ADULT	-0.022	0.042	-0.105	-0.022	0.06	-0.022
AV MH MISPER MINOR	0.538	0.279	-0.002	0.536	1.092	0.531
AV MH MISPER ADULT t-1	-0.095	0.031	-0.157	-0.095	-0.034	-0.094
AV MH MISPER MINOR t-1	-0.751	0.268	-1.281	-0.749	-0.229	-0.746
PERRY BARR	0.104	0.03	0.045	0.104	0.163	0.104
ASTON	0.126	0.103	-0.076	0.125	0.327	0.125
COVENTRY CENTRAL	-0.326	0.123	-0.568	-0.325	-0.085	-0.325
PERRY BARR t-1	-0.038	0.031	-0.098	-0.038	0.022	-0.038
ASTON t-1	0.318	0.106	0.11	0.317	0.527	0.317
COVENTRY CENTRAL t-1	0.122	0.125	-0.13	0.124	0.362	0.128
SUTTON COLDFIELD	-0.043	0.061	-0.162	-0.043	0.076	-0.043
SUTTON COLDFIELD t-1	0.014	0.038	-0.061	0.014	0.09	0.014
WOLVERHAMPTON CENTRAL	-0.013	0.055	-0.121	-0.013	0.094	-0.012
WOLVERHAMPTON CENTRAL t-1	0.155	0.059	0.04	0.154	0.27	0.154
COVID D	-1.084	0.26	-1.602	-1.081	-0.58	-1.076
Size for Nbinomial Zero Inflated Obs	3.134	0.630	2.054	3.080	4.512	2.987
Zero-probability Parameter	0.571	0.008	0.555	0.571	0.587	0.571
SD for MH_Crimes t-1	0.010	0.006	0.004	0.008	0.028	0.006
SD for Ward	0.011	0.008	0.004	0.008	0.031	0.006
SD for Month	0.011	0.007	0.004	0.009	0.030	0.006
Ward Model	Besag					
Random Effects	Month & Lagged MH IO			Random Walk		
Deviance Information Criterion (DIC)	9204.17					
Watanabe-Akaike information criterion (WAIC)	9204.17					


(Intercept)
Aston
Aston (t-1)
Av Mh Crimes (t-1)
Av Mh Misper Adult
Av Mh Misper Adult (t-1)
Av Mh Misper Minor
Av Mh Misper Minor (t-1)
Av Total Inc (t-1)
Count Mh Inst in Ward
Coventry Central
Coventry Central (t-1)
Covid d
Crime Asb
Crime Damage
Crime Drugs
Crime Harass
Crime Other
Crime Theft
Crime Violent
I Max Mh Crime t Max Mh Crimes Total
Perry Barr
Perry Barr (t-1)
Sutton Coldfield
Sutton Coldfield (t-1)
Wolverhampton Central
Wolverhampton Central (t-1)
density
x

BYM Model	Mean	SD	0.025 Quant	Median	0.975 Quant	Mode
(Intercept)	0.688	50.785	-99.02	0.687	100.314	0.688
COUNT MH INST IN WARD	0.169	0.052	0.068	0.168	0.272	0.167
CRIME ASB	0.021	0.031	-0.041	0.021	0.082	0.021
CRIME DAMAGE	0.007	0.007	-0.007	0.007	0.021	0.007
CRIME DRUGS	-0.023	0.009	-0.041	-0.023	-0.004	-0.022
CRIME HARASS	0.007	0.007	-0.006	0.007	0.02	0.007
CRIME OTHER	0.004	0.004	-0.004	0.004	0.012	0.004
CRIME VIOLENT	0.013	0.003	0.006	0.013	0.019	0.013
CRIME THEFT	-0.01	0.002	-0.013	-0.01	-0.006	-0.01
I(Max MH IO t/MAX MH IO TOTAL)	0.185	0.252	-0.317	0.187	0.674	0.192
AV TOTAL INC t-1	0.001	0	0	0.001	0.001	0.001
AV MH IO t-1	-0.003	0.054	-0.106	-0.005	0.107	-0.009
AV MH MISPER ADULT	-0.013	3.659	-7.197	-0.013	7.166	-0.013
AV MH MISPER MINOR	0.003	21.895	-42.984	0.003	42.955	0.003
AV MH MISPER ADULT t-1	-0.098	4.022	-7.995	-0.098	7.792	-0.098
AV MH MISPER MINOR t-1	-0.628	18.793	-37.525	-0.629	36.237	-0.628
PERRY BARR	0.118	4.658	-9.027	0.118	9.256	0.118
ASTON	-0.112	14.369	-28.323	-0.113	28.075	-0.112
COVENTRY CENTRAL	-0.153	12.445	-24.588	-0.154	24.261	-0.153
PERRY BARR t-1	-0.026	6.191	-12.181	-0.026	12.118	-0.026
ASTON t-1	0.123	16.598	-32.465	0.123	32.684	0.123
COVENTRY CENTRAL t-1	-0.065	7.682	-15.148	-0.066	15.005	-0.065
SUTTON COLDFIELD	0.075	5.25	-10.232	0.075	10.373	0.075
SUTTON COLDFIELD t-1	-0.044	5.935	-11.695	-0.044	11.598	-0.044
WOLVERHAMPTON CENTRAL	0.152	9.836	-19.158	0.152	19.447	0.152
WOLVERHAMPTON CENTRAL t-1	0.04	4.673	-9.134	0.04	9.207	0.04
COVID D	-0.879	19.093	-38.364	-0.879	36.575	-0.879
Jan	0.101	27.012	-52.932	0.1	53.09	0.101
Feb	0.465	21.501	-41.75	0.464	42.644	0.465
Mar	-0.108	15.039	-29.635	-0.108	29.395	-0.108
May	0.158	20.104	-39.313	0.157	39.595	0.158
Jun	0.306	16.798	-32.673	0.306	33.258	0.306
Jul	-0.042	24.895	-48.919	-0.043	48.795	-0.042
Aug	-0.171	25.984	-51.186	-0.172	50.801	-0.171
Sept	0.298	19.472	-37.932	0.297	38.496	0.298
Oct	-0.085	25.735	-50.613	-0.086	50.399	-0.085
Nov	-0.021	25.118	-49.337	-0.022	49.254	-0.021
Dec	0.417	27.994	-54.544	0.416	55.333	0.417
Size for Nbinomial Zero Inflated Obs	4.8593	1.4359	2.8936	4.5532	8.4078	4.0075
Zero-probability Parameter	0.5713	0.0081	0.5555	0.5712	0.5873	0.5709
SD for MH Crimes t-1	0.0107	0.0063	0.0039	0.0089	0.0275	0.0066
SD for Ward (idd component)	0.2814	0.0540	0.1902	0.2762	0.4014	0.2660
SD for Ward (spatial component)	0.0332	0.0226	0.0118	0.0262	0.0948	0.0180
Precision for Month	0.0113	0.0067	0.0039	0.0094	0.0293	0.0069
Ward Model	BYM					

Random Effects	Month & Lagged MH IO	Random Walk
Deviance Information Criterion (DIC)	9156.46	
Watanabe-Akaike information criterion (WAIC)	9160.35	



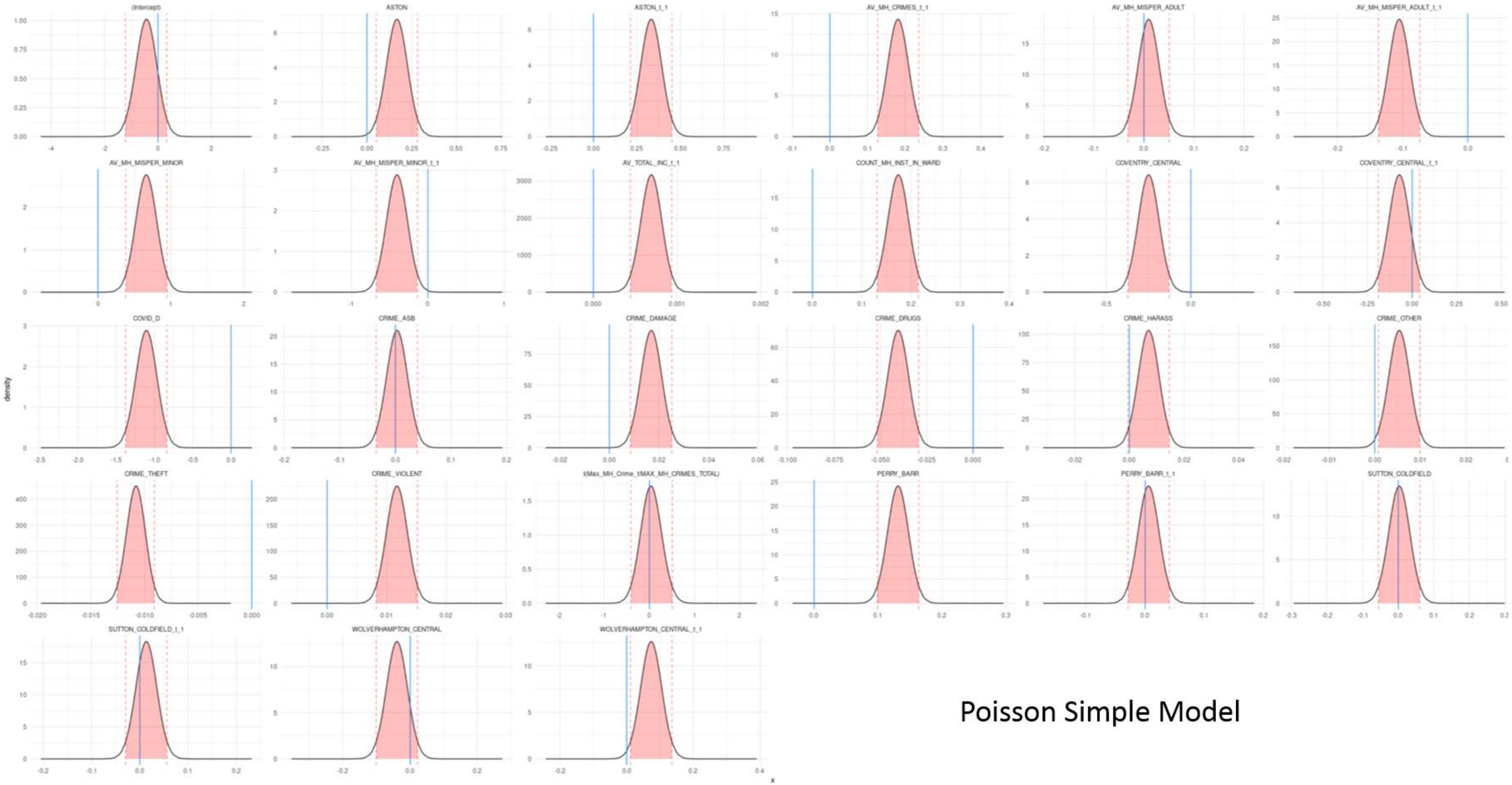
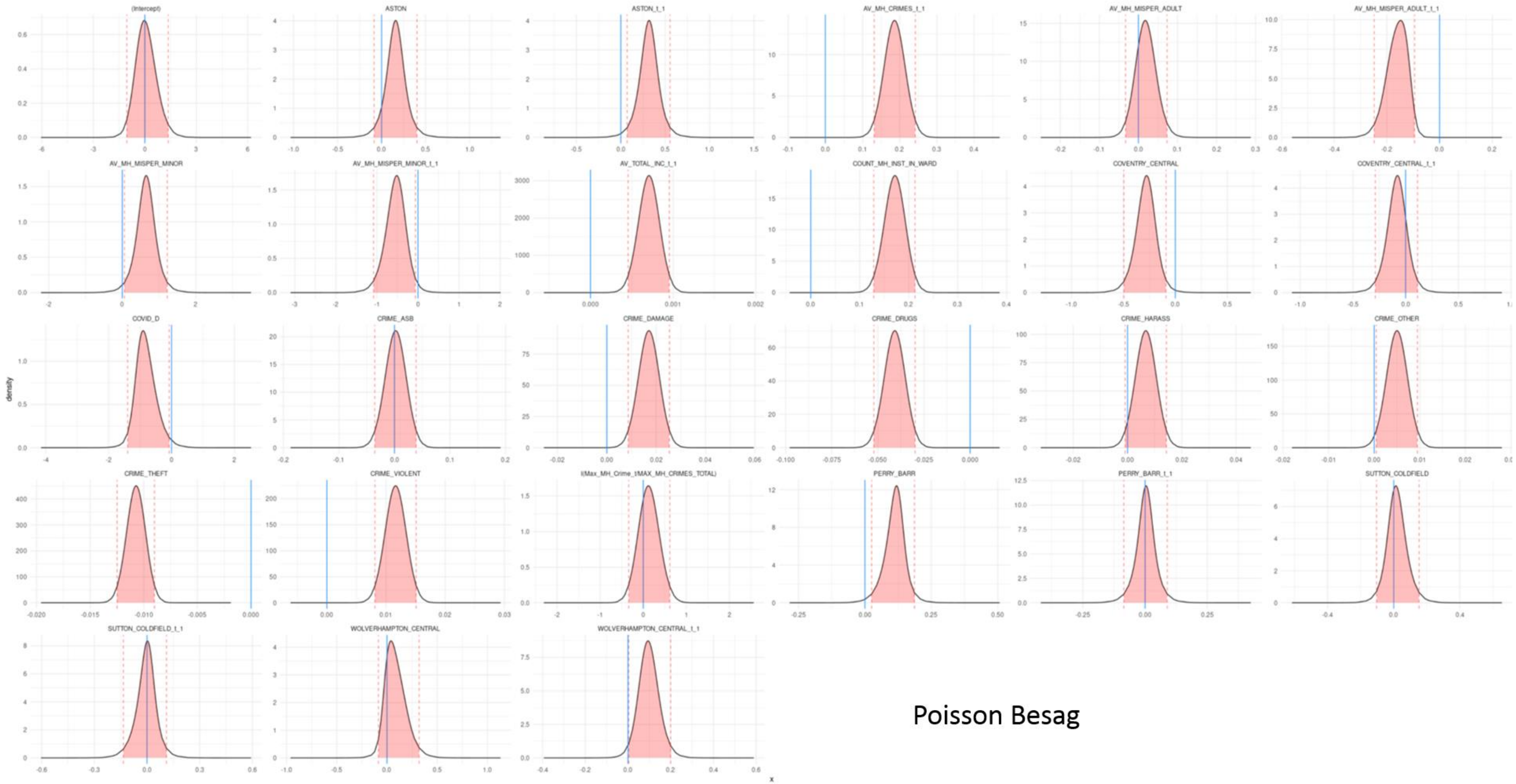
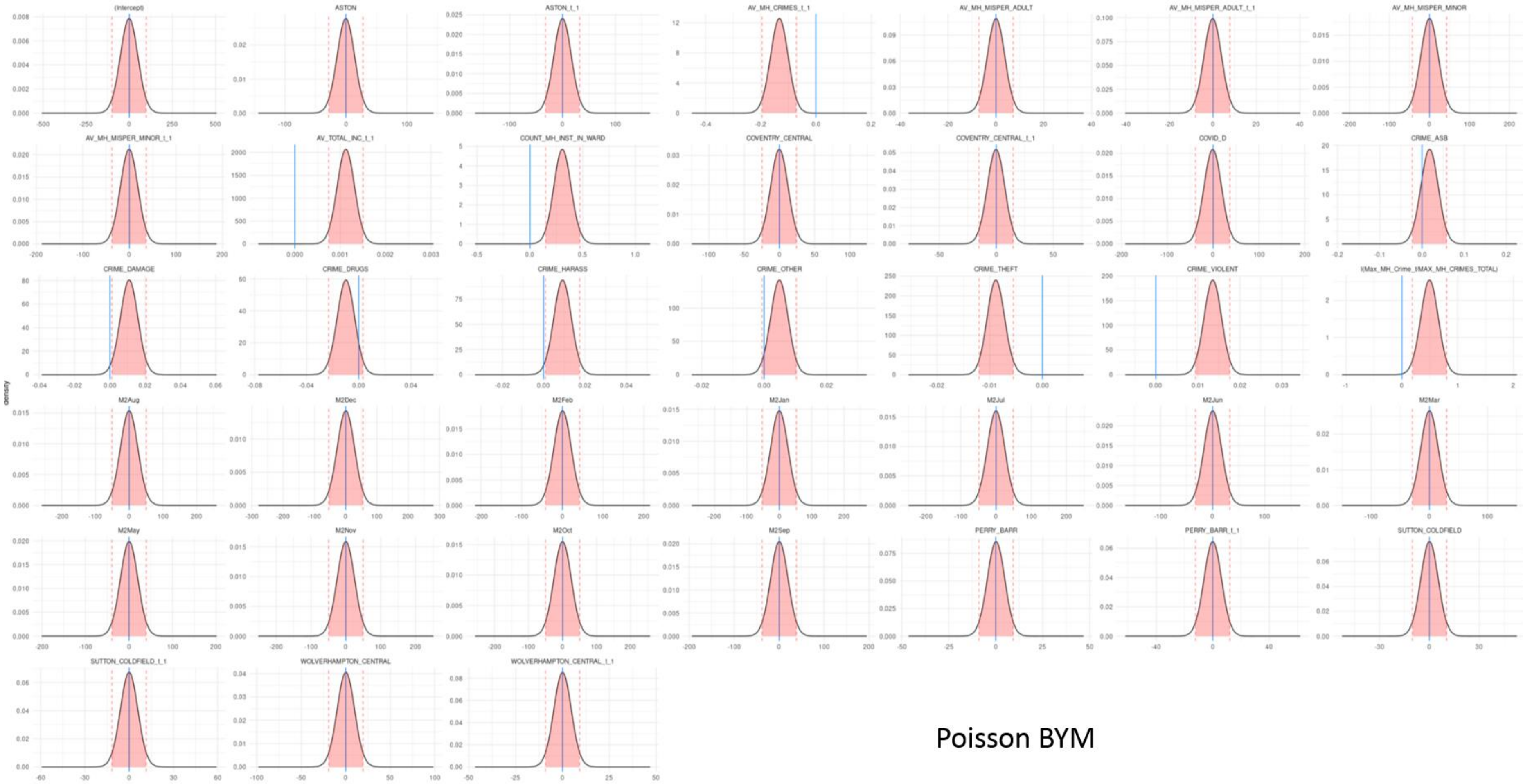


Figure 35 Variables for Poisson Models of Crimes Associated With Mental Health Issues



Poisson Besag


(Intercept)
ASTON
ASTON_t_1
AV_MH_CRIMES_t_1
AV_MH_MISPER_ADULT
AV_MH_MISPER_ADULT_t_1
AV_MH_MISPER_MINOR
AV_MH_MISPER_MINOR_t_1
AV_TOTAL_INC_t_1
COUNT_MH_INST_IN_WARD
COVENTRY_CENTRAL
COVENTRY_CENTRAL_t_1
COVID_D
CRIME_ASB
CRIME_DAMAGE
CRIME_DRUGS
CRIME_HARASS
CRIME_OTHER
CRIME_THEFT
CRIME_VIOLENT
I(Max_MH_Crime_t/MAX_MH_CRIMES_TOTAL)
density
M2Aug
M2Dec
M2Feb
M2Jan
M2Jul
M2Jun
M2Mar
M2May
M2Nov
M2Oct
M2Sep
PERRY_BARR
PERRY_BARR_t_1
SUTTON_COLDFIELD
SUTTON_COLDFIELD_t_1
WOLVERHAMPTON_CENTRAL
WOLVERHAMPTON_CENTRAL_t_1

Poisson BYM

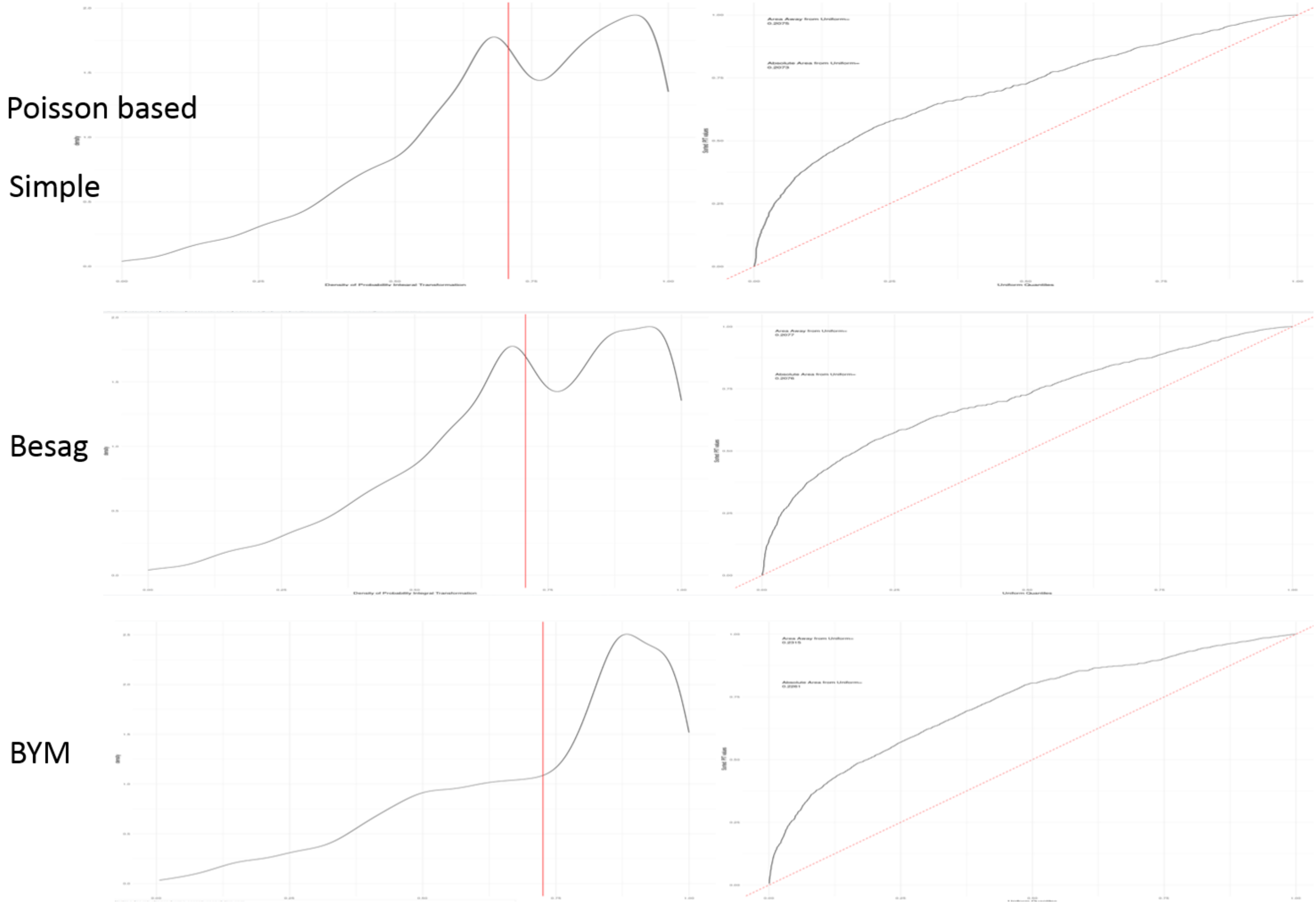


Figure 36 PIT Diagnosis Poisson Models

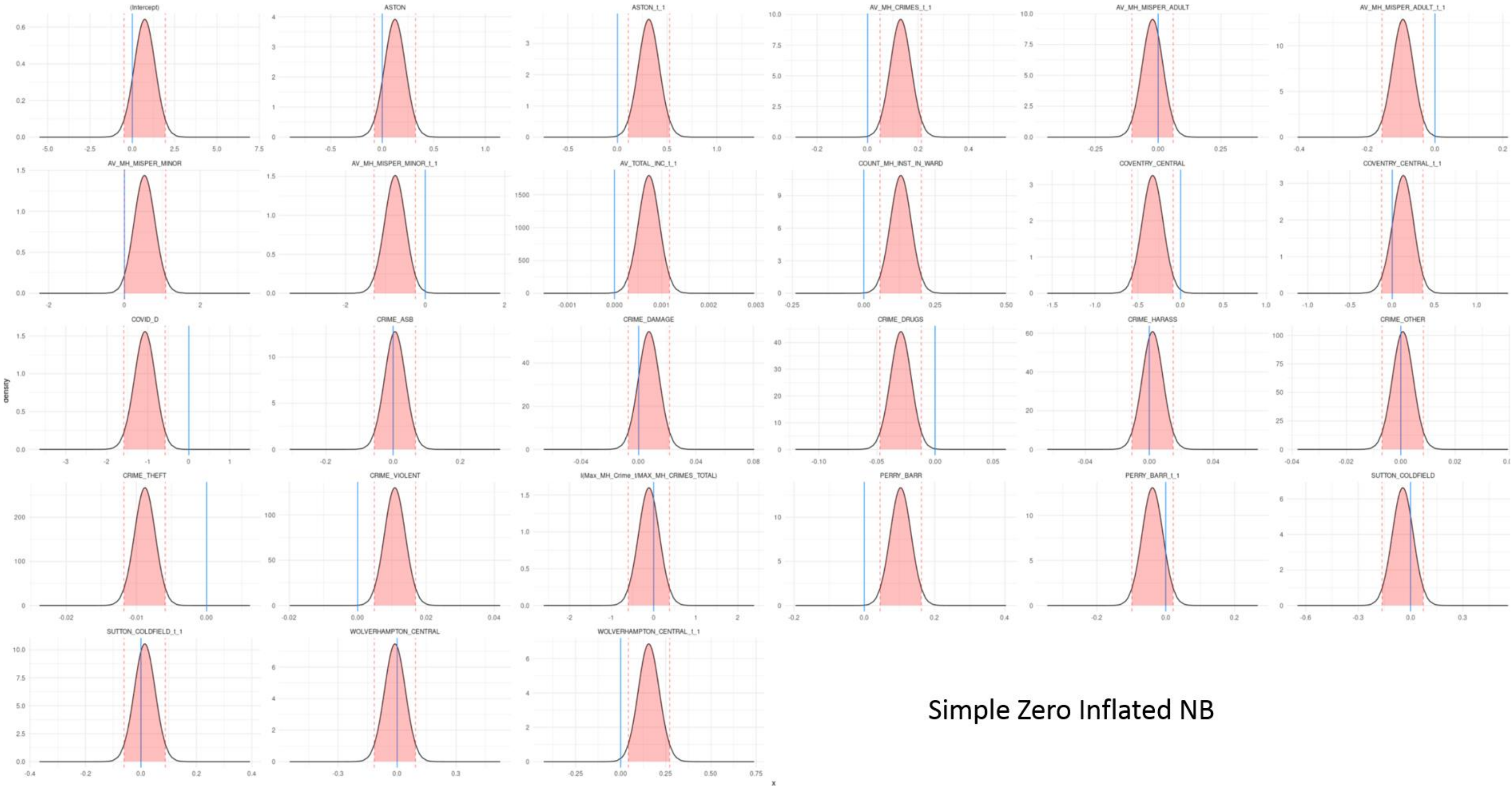
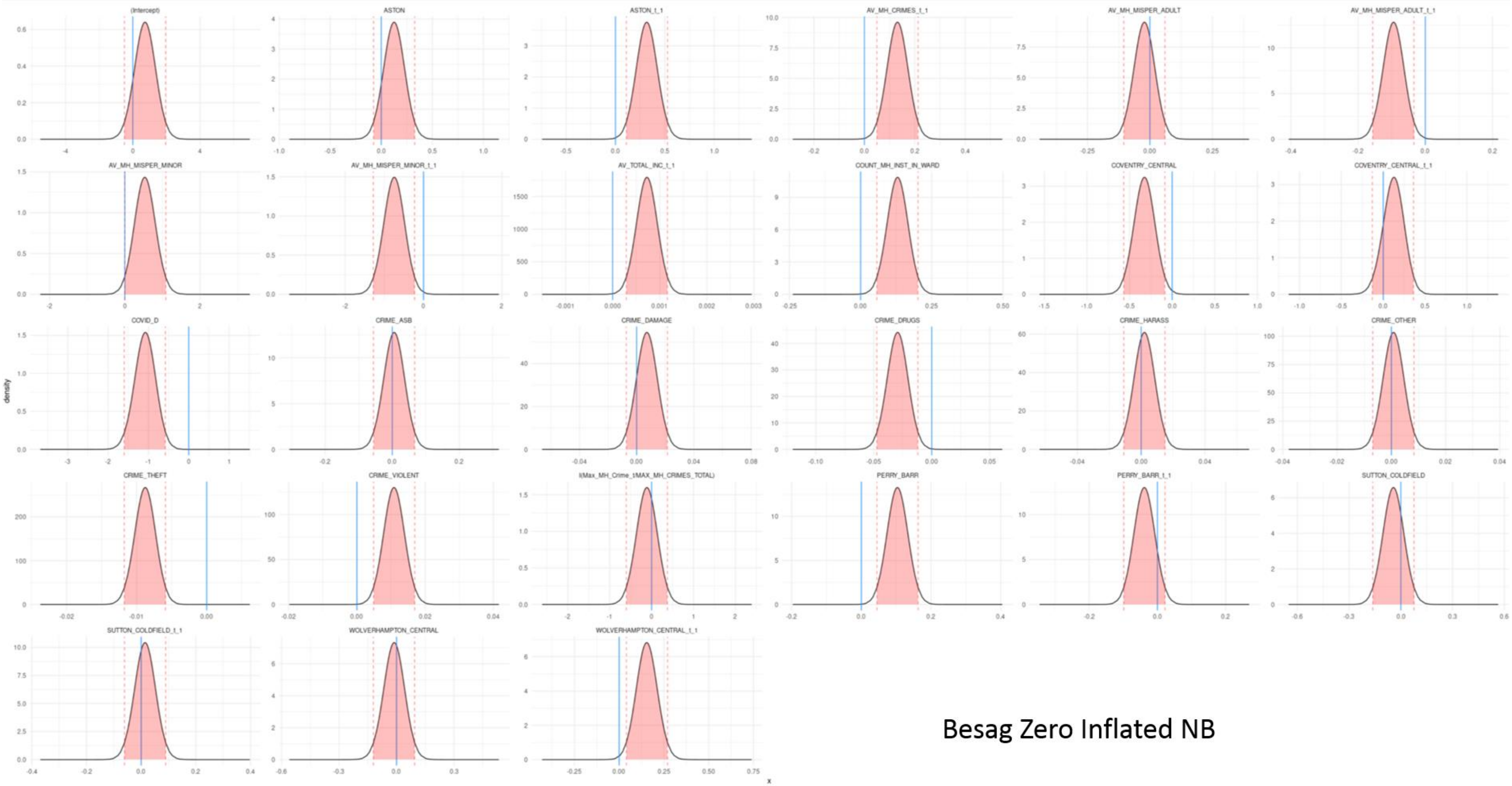
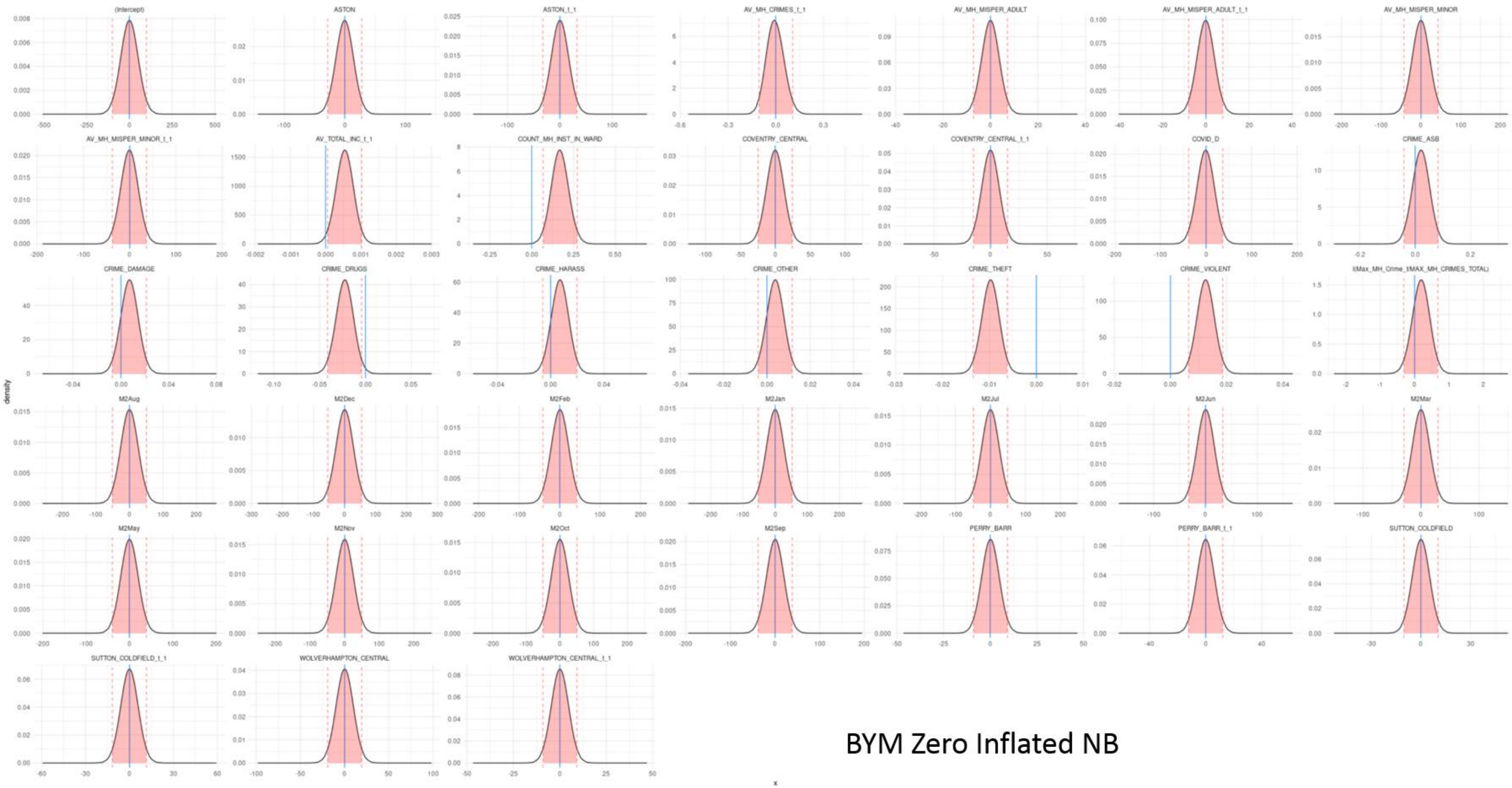


Figure 37 Variables for Zero Inflated Models



Besag Zero Inflated NB



BYM Zero Inflated NB

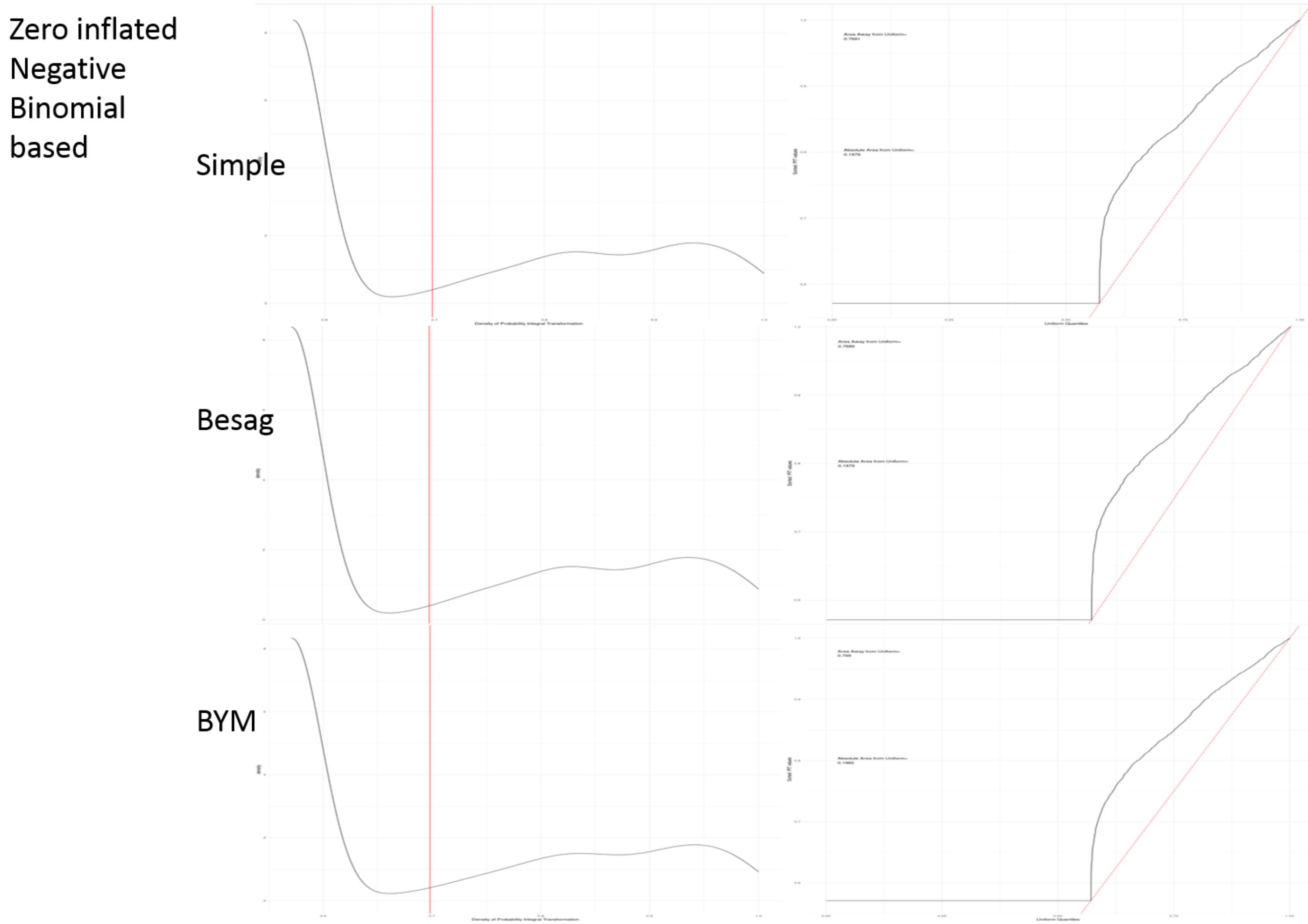


Figure 38 PIT diagnosis for Zero Inflated Negative Binomial Models

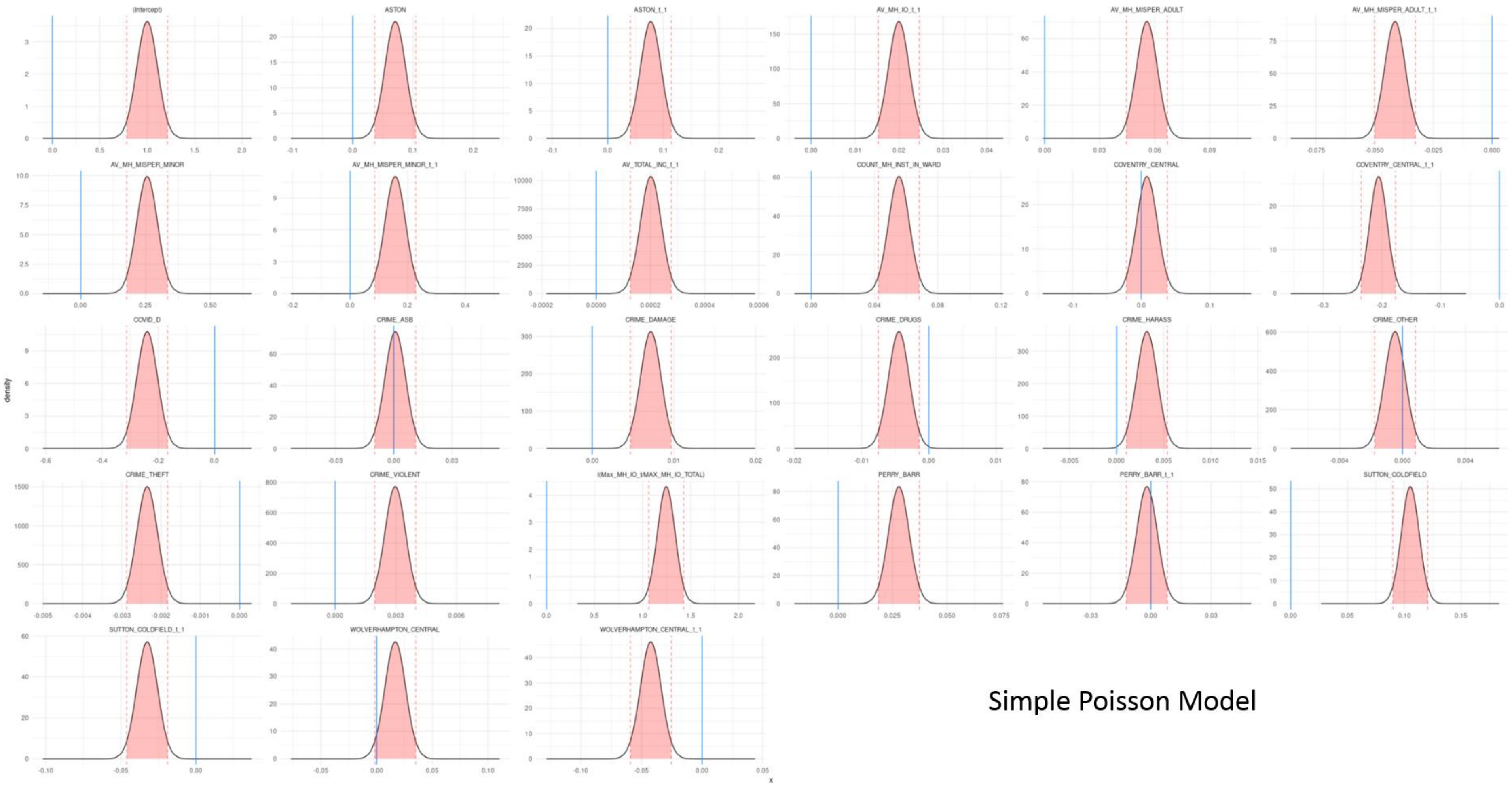
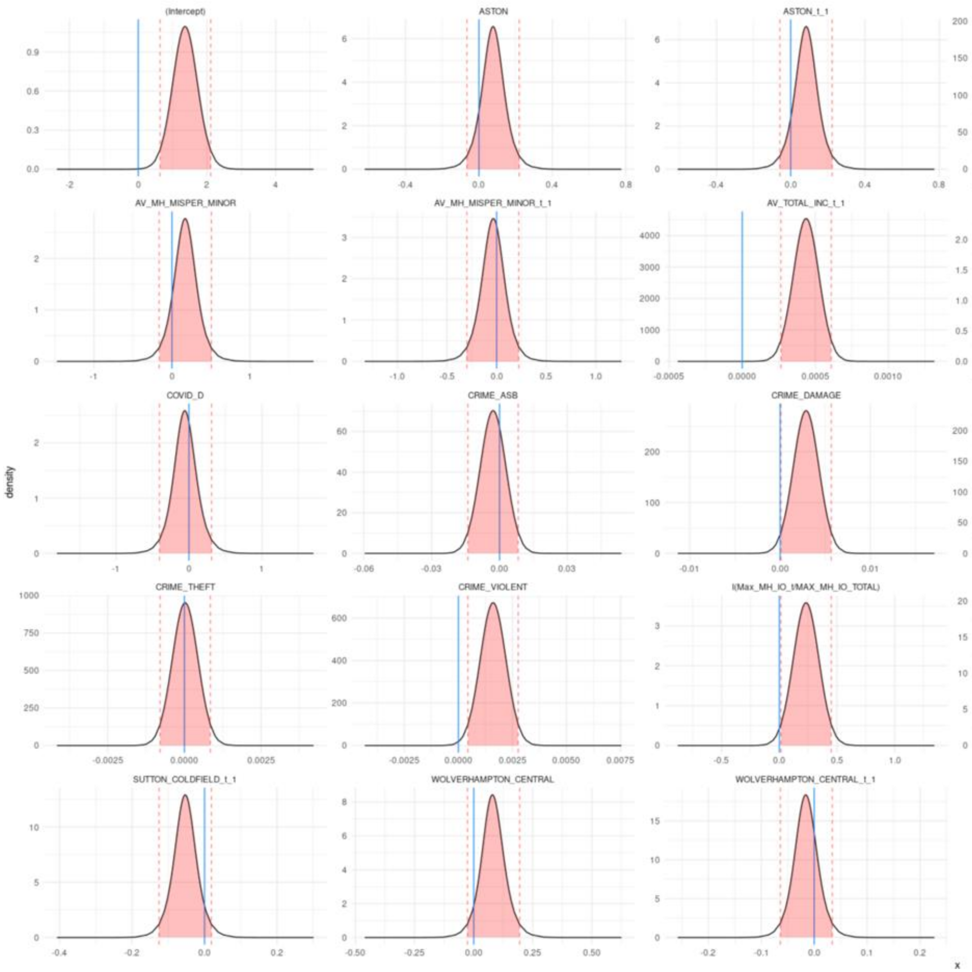
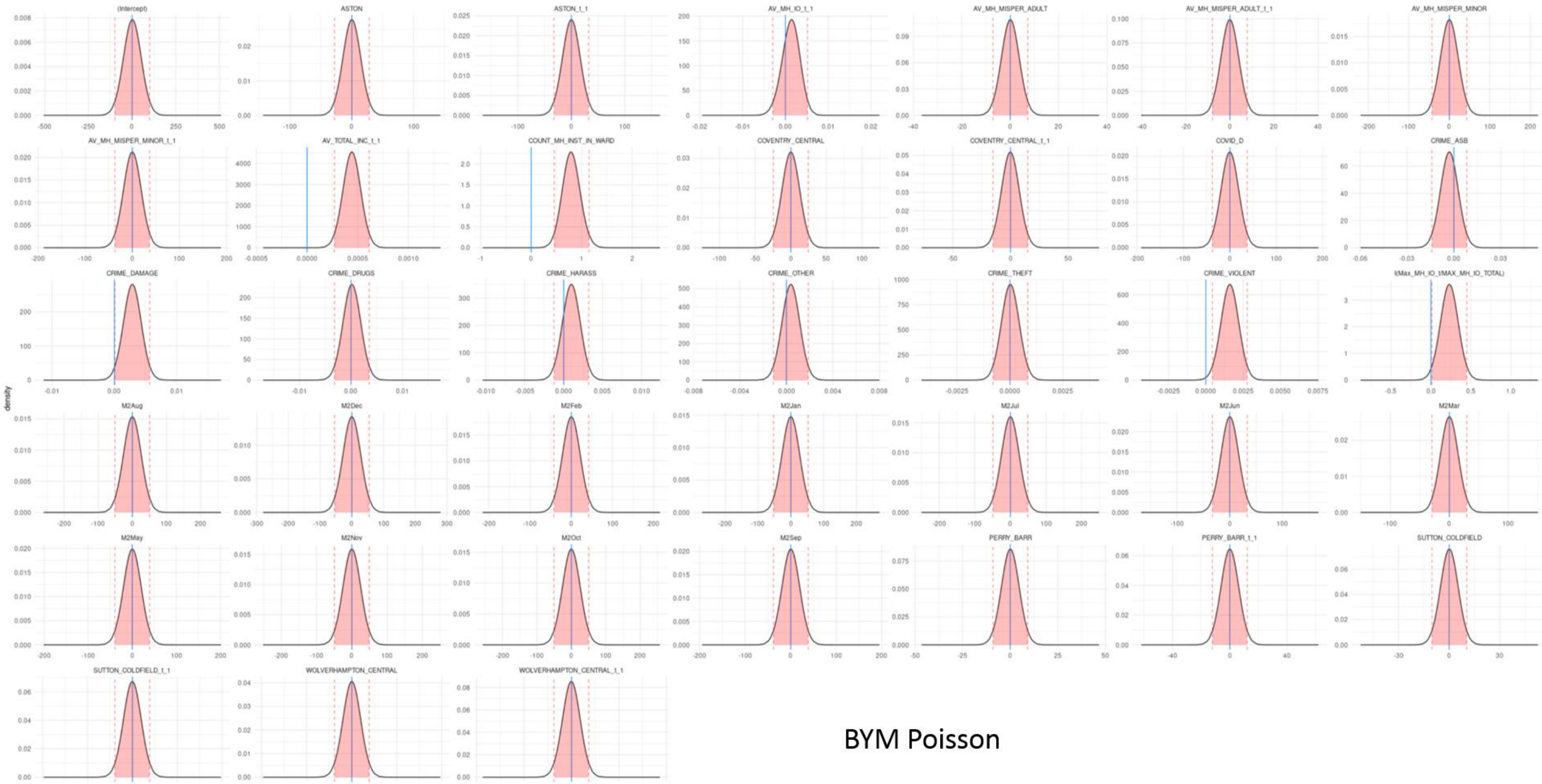


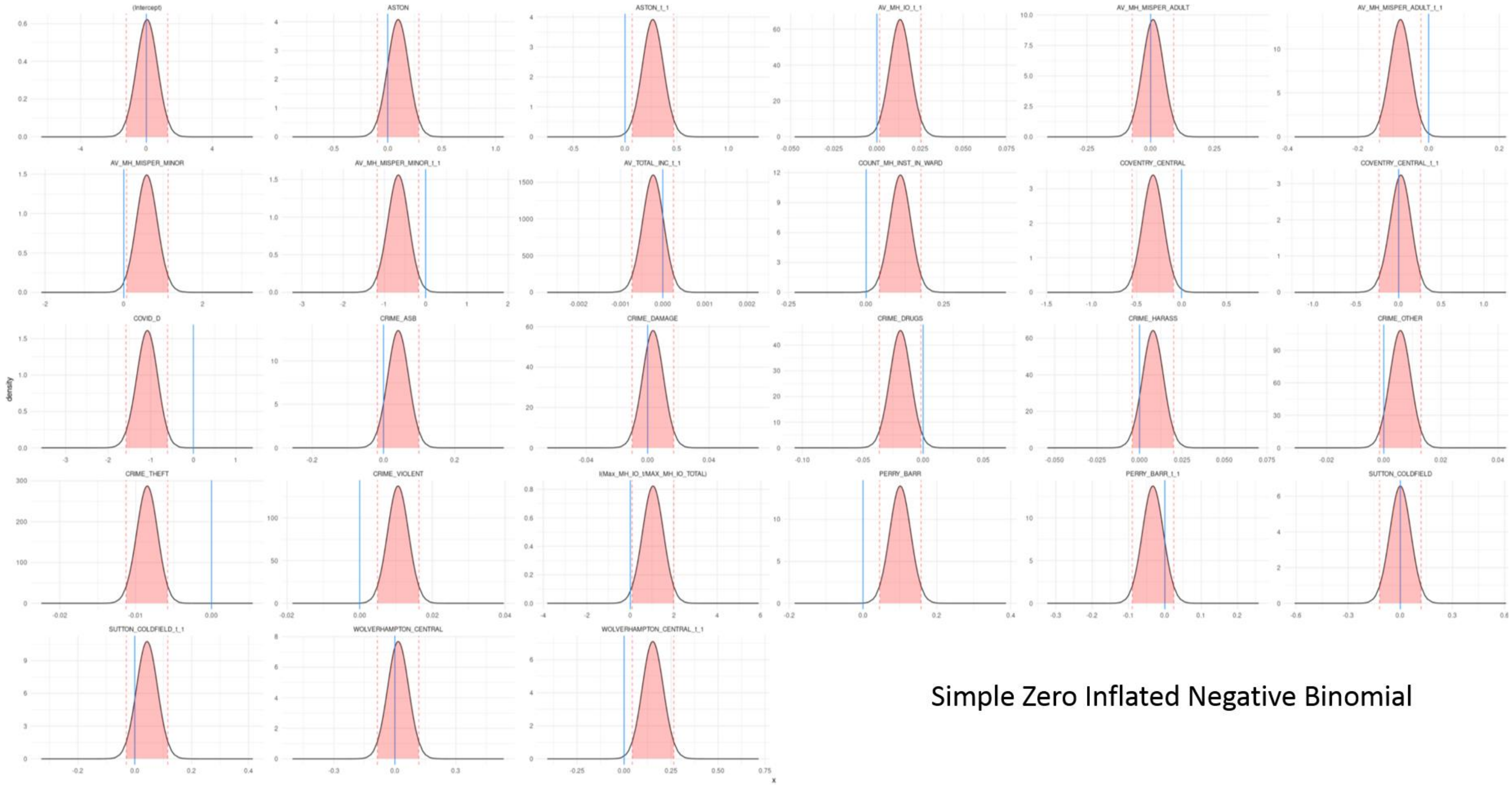
Figure 39 Coefficients for Simple Poisson and Zero Inflated Models of Incidents Involving Mental Health Factors



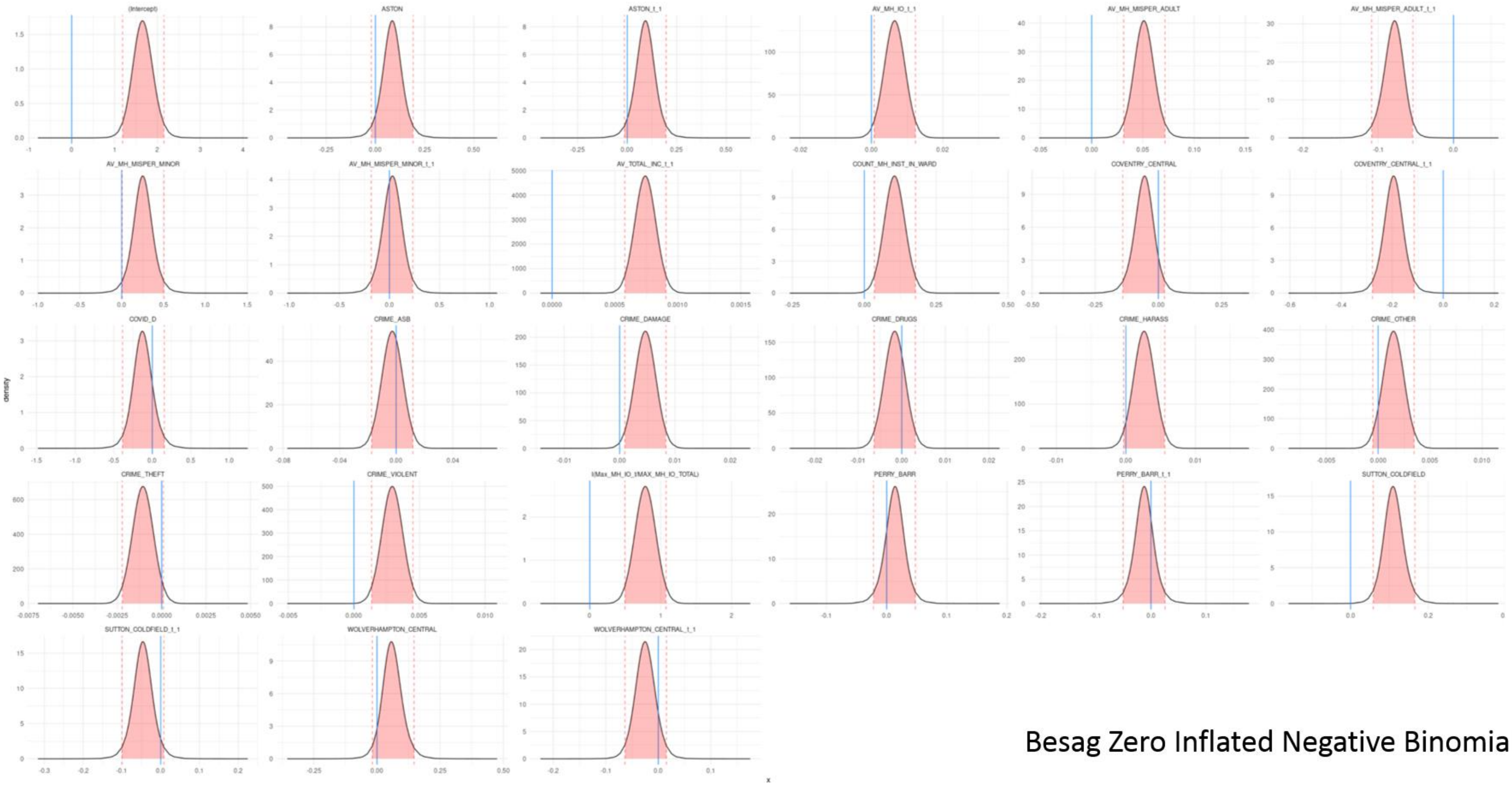
Besag Poisson


(Intercept)
ASTON
ASTON_t_1
AV_MH_IO_t_1
AV_MH_MISPER_ADULT
AV_MH_MISPER_ADULT_t_1
AV_MH_MISPER_MINOR
AV_MH_MISPER_MINOR_t_1
AV_TOTAL_INC_t_1
COUNT_MH_INST_IN_WARD
COVENTRY_CENTRAL
COVENTRY_CENTRAL_t_1
COVID_D
CRIME_ASB
CRIME_DAMAGE
CRIME_DRUGS
CRIME_HARASS
CRIME_OTHER
CRIME_THEFT
CRIME_VIOLENT
I(Max_MH_IO_t/MAX_MH_IO_TOTAL)
density
M2Aug
M2Dec
M2Feb
M2Jan
M2Jul
M2Jun
M2Mar
M2May
M2Nov
M2Oct
M2Sep
PERRY_BARR
PERRY_BARR_t_1
SUTTON_COLDFIELD
SUTTON_COLDFIELD_t_1
WOLVERHAMPTON_CENTRAL
WOLVERHAMPTON_CENTRAL_t_1

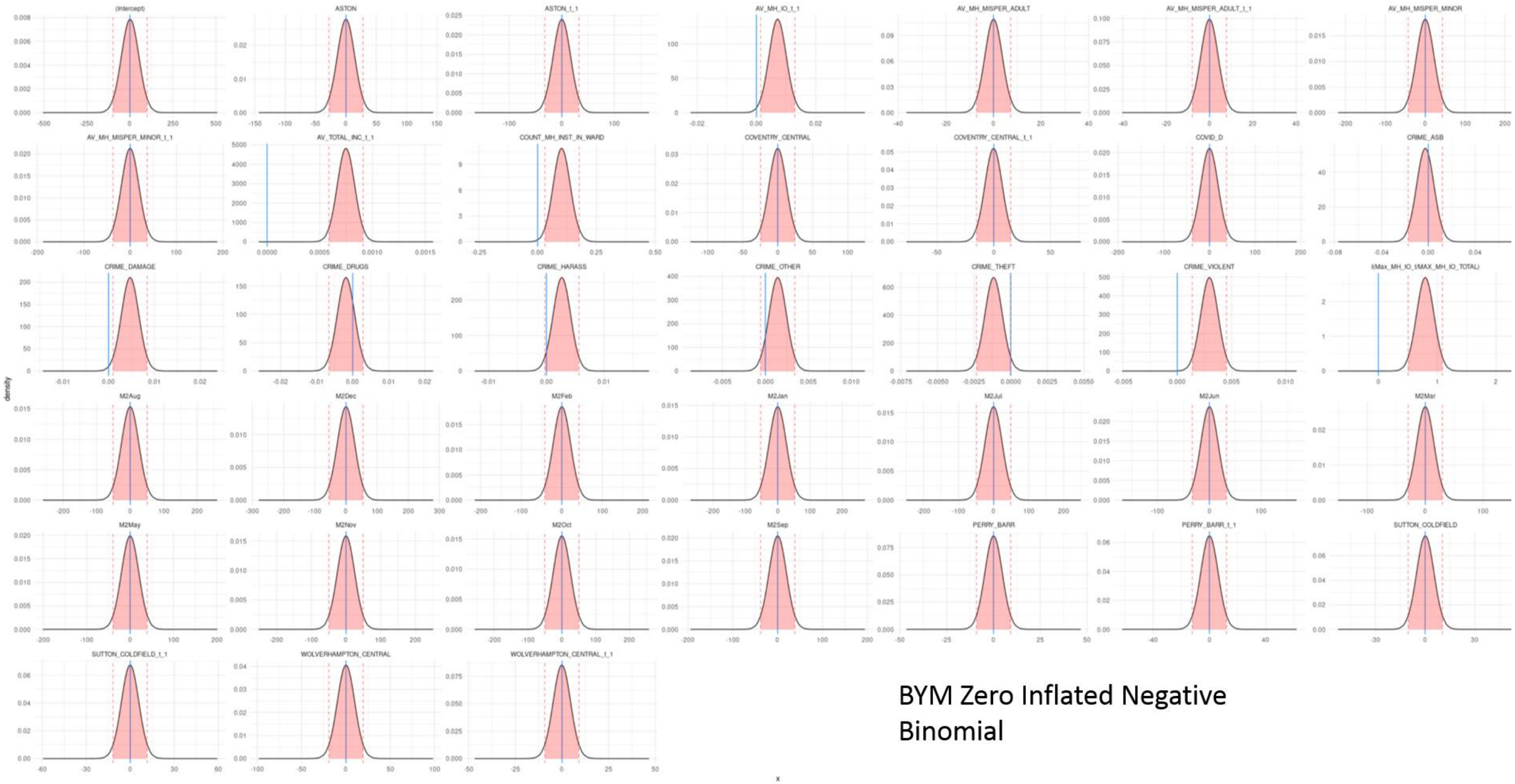
BYM Poisson



Simple Zero Inflated Negative Binomial



Besag Zero Inflated Negative Binomial



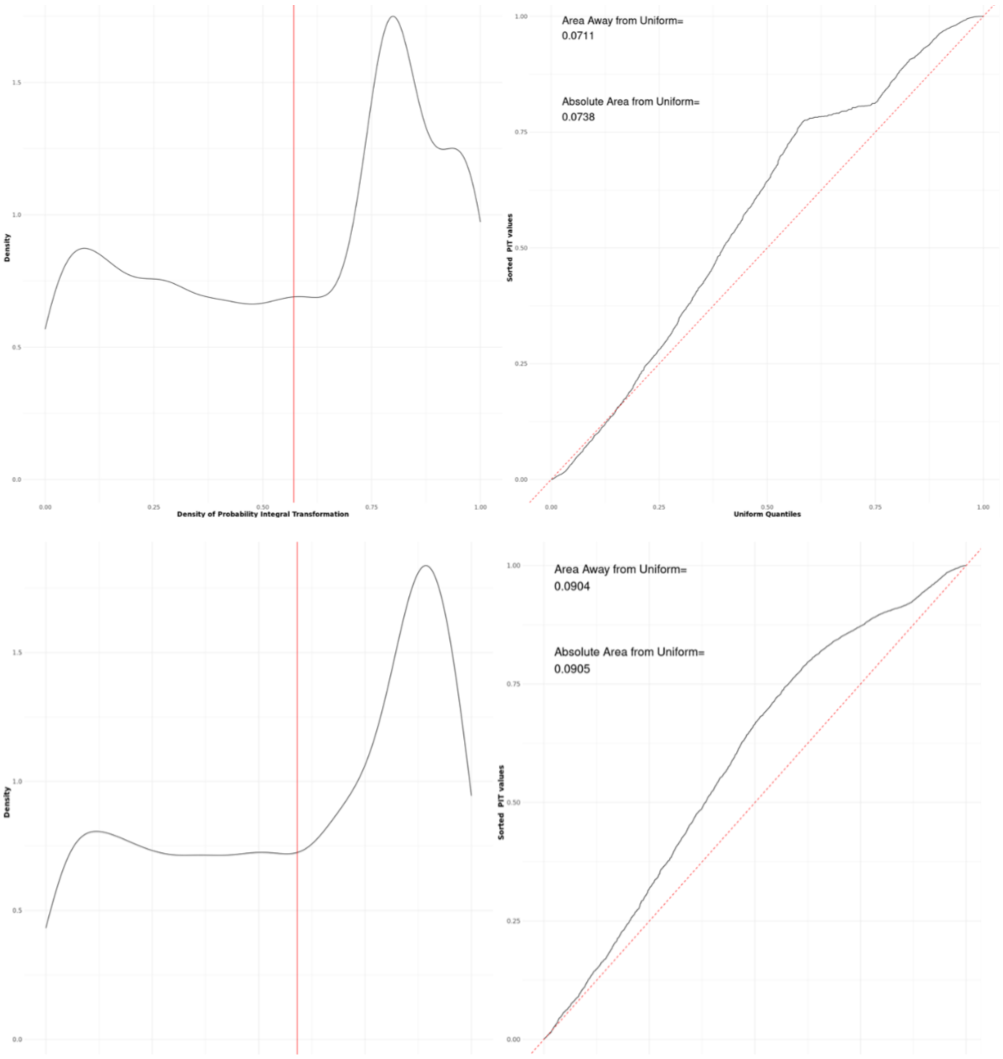
BYM Zero Inflated Negative Binomial

Diagnostics

The models have a number of diagnostics to consider the applicability of the assumptions associated with the modelling. The Poisson models all have dispersion parameters above 1, with the BYM dispersion being lower at 1.03, suggesting that the dispersion is dealt with by the BYM specification.

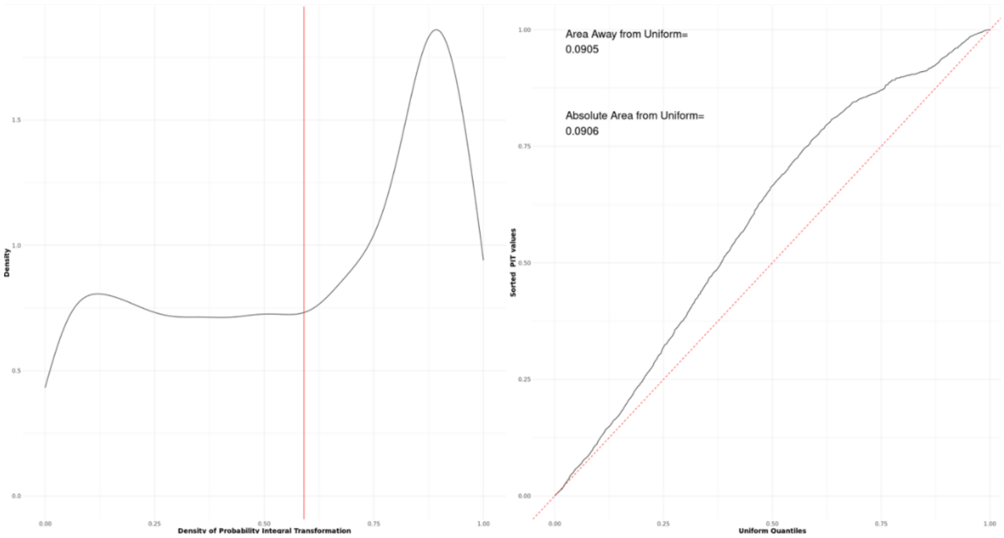
Incidents

The PIT diagnosis suggests that there is some residual over-dispersion despite the estimate from the previous tests.



Simple Poisson

Poisson
Besag Model



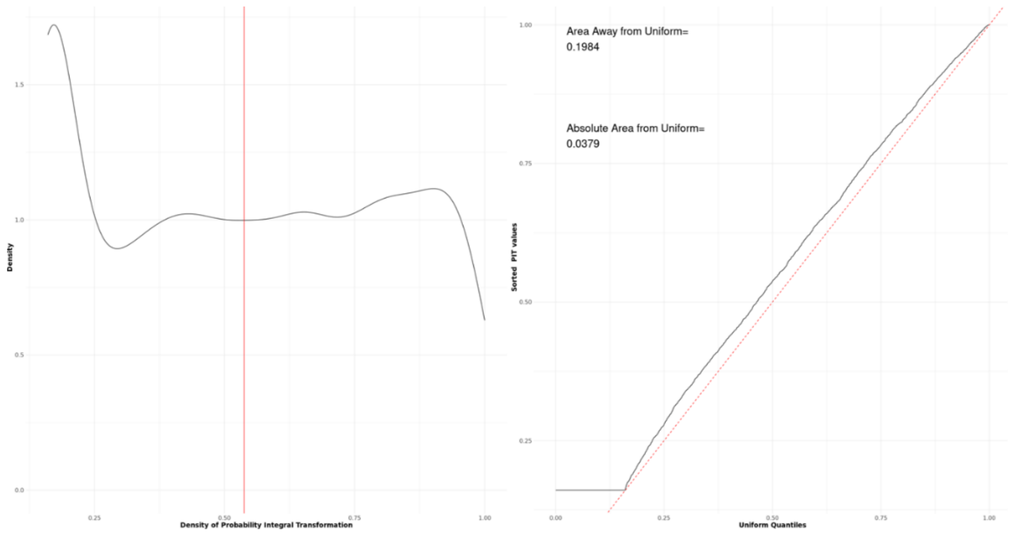
Poisson
BYM Model

Figure 40 Poisson Model PIT Diagnostics

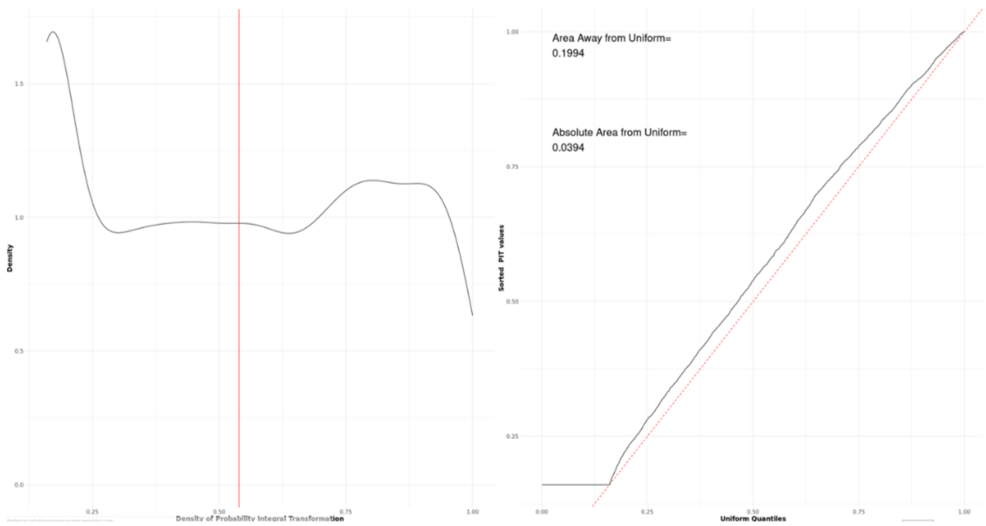
One can see from the right hand lump on all the PITs that the Poisson models are over-dispersed, i.e. that the variance is too high, and that the over-dispersion is present irrespective of the model specification.

A different issue reveals itself with the zero inflated models, there is some over-dispersion though very little, but the zeros are potentially a little too high as there is a peak near 0.

The horizontal line in the PIT-QQ plot exaggerates the area under the curve. A correction factor of the square that has the size of the horizontal line is necessary bounded by the 45◦ line is used. The area of this square is known as it is has the length of the minimum PIT. The absolute measure is unaffected. For the simple model this correction is 0.326, for the Besag model it is 0.327 and the BYM model it is 0.326. Thus the areas become 0.443, 0.443 and 0.443 respectively.[1]

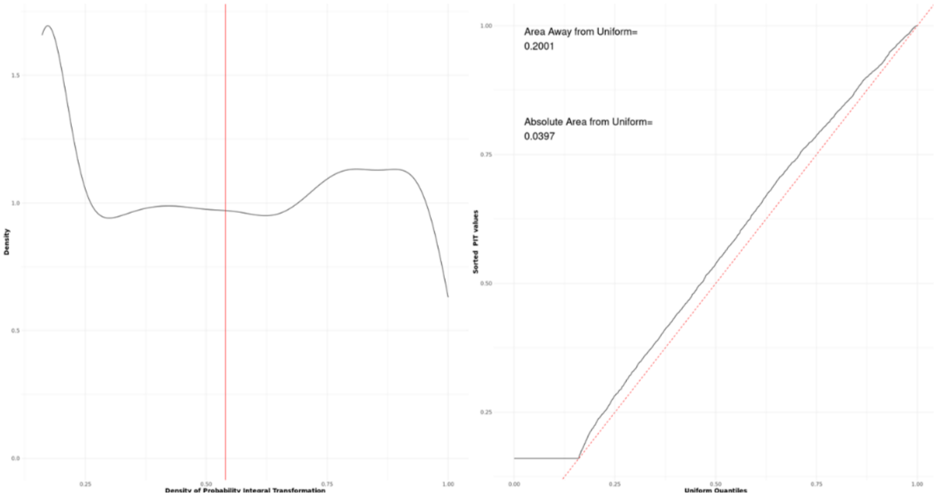


Simple Zero Inflated Negative Binomial



Zero Inflated Negative Binomial Besag Model

[1] This is a new metric which I feel needs a little more analysis.



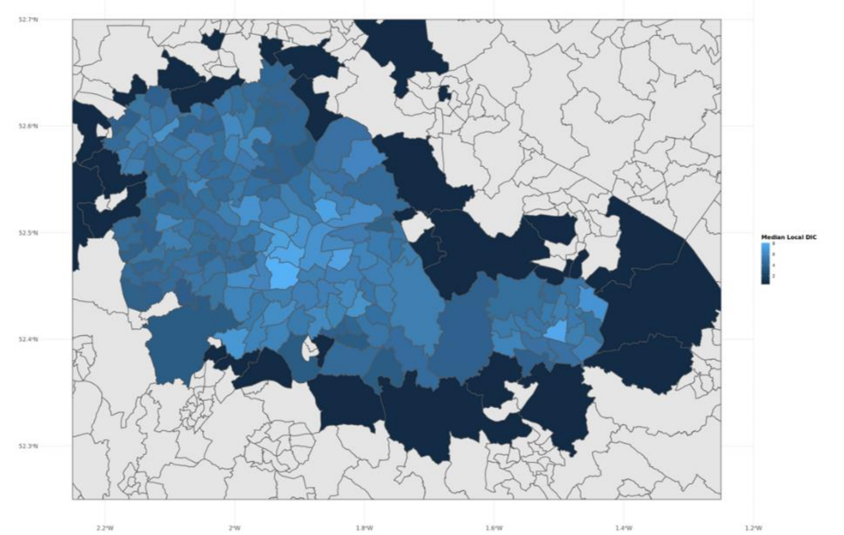
Zero Inflated
Negative Binomial
BYM Model

Figure 41 Zero Inflated Negative Binomial PIT Diagnostics

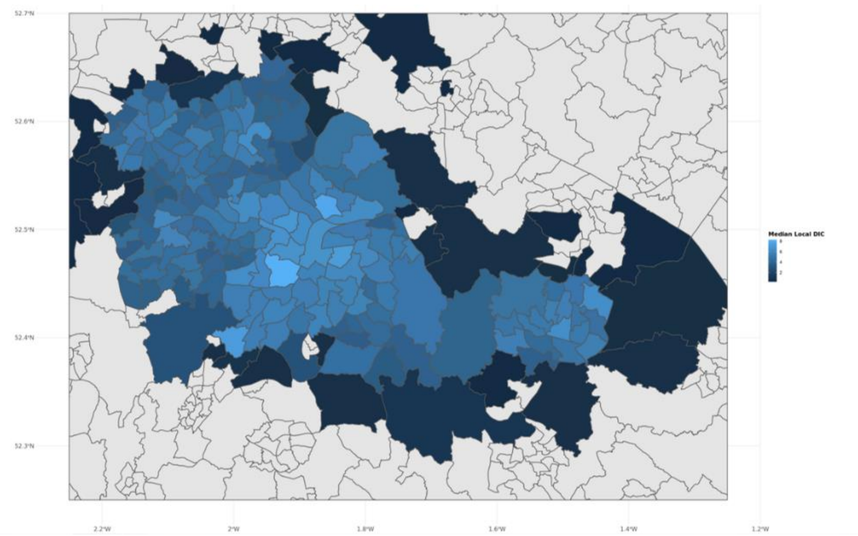
In addition to these PIT diagnostics that suggest that the zero inflated negative binomial is the best fit, we can examine the map of localised deviance information criteria. This can be aggregated across space and time to examine where the model fits least well and in what locations deviations away from expectations occur.

The DIC is often used in a manner analogous to the AIC in frequentist statistics. The Appendix reports the DIC and WAIC for the models. These support the BYM models in general with the Besag and simpler models being similar in results. This could be expected given the similarities of the model coefficients. However using the results of Spiegelhalter et al. (2002), the DIC can be split to see the individual observation's contributions. These individual elements can be mapped against the locations, giving geographical realisations of the model's adequacy.

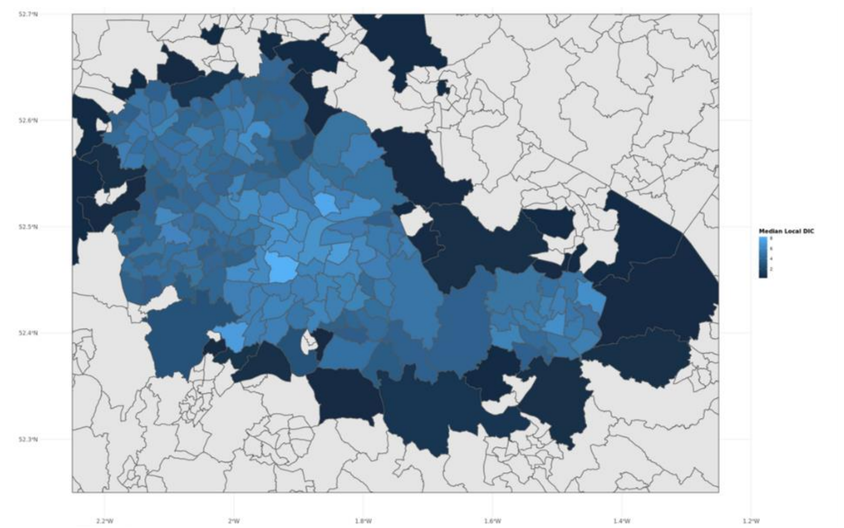
The darker colours reflect better fits and in some areas, for example towards the northern end of the WMP area around Wolverhampton and Walsall and more southerly areas such as King's Heath the models improve by moving towards the zero inflated model. An analysis through time was also performed and the results were similar with considerable stability over time.



Simple Poisson
Local DIC



Poisson Besag Model
Local DIC



Poisson BYM Model
Local DIC

Figure 42 Localised DICs for Poisson Modelling of Incidents

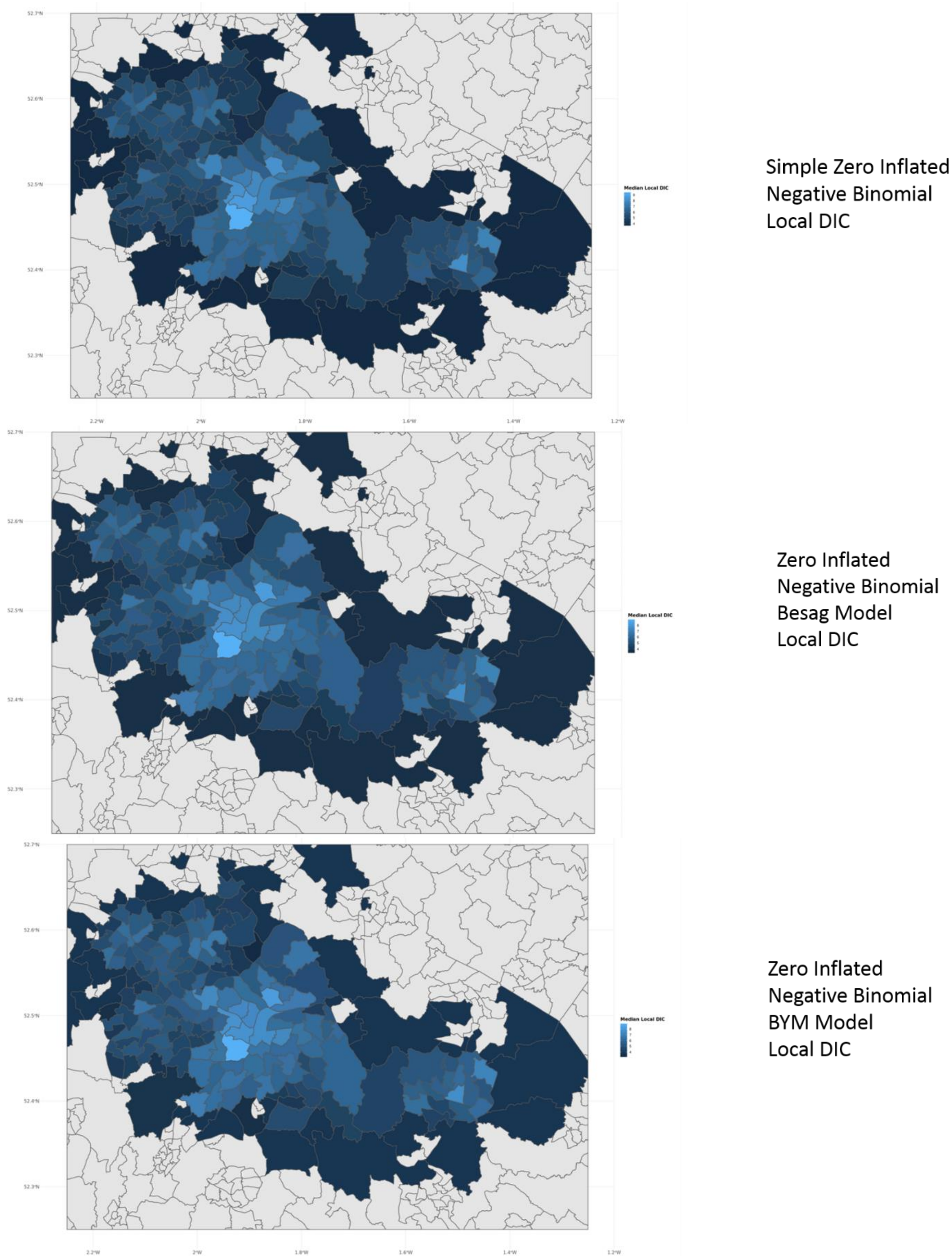
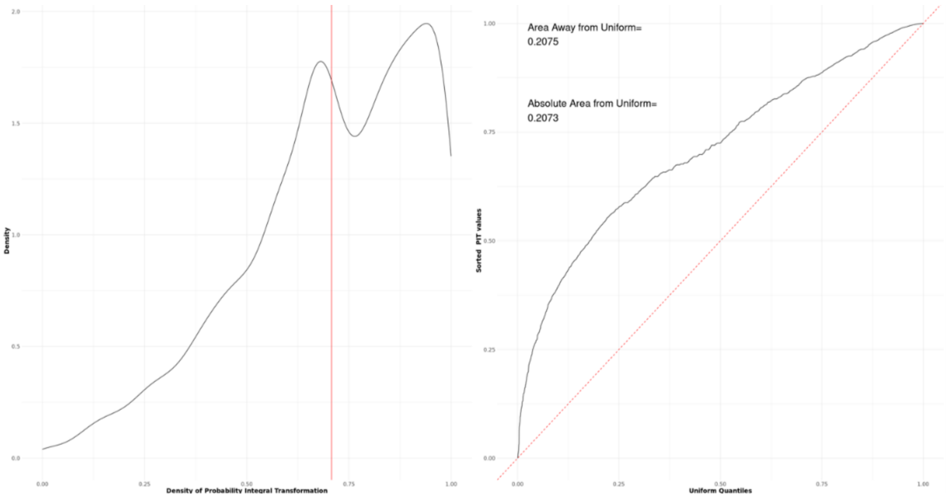


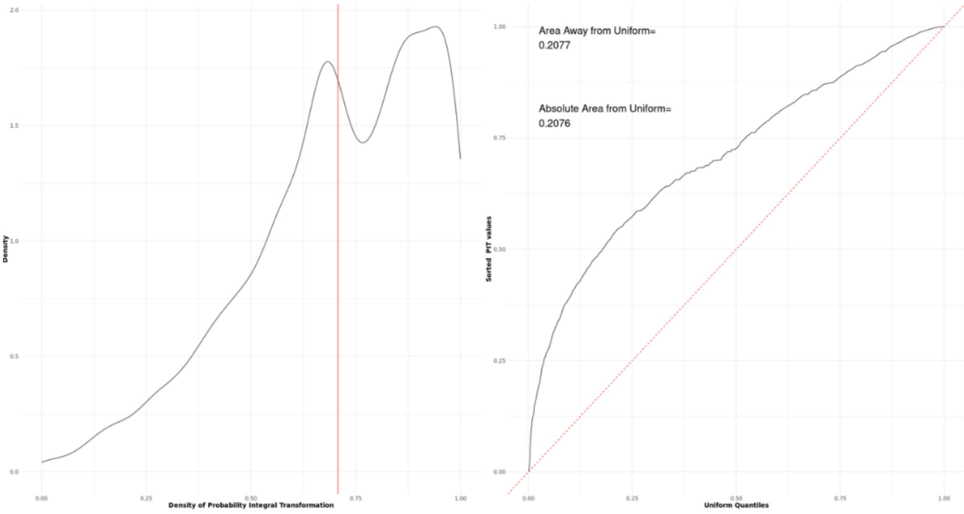
Figure 43Local DICs for Zero Inflated Negative Binomial Models of Incidents

Crimes Models

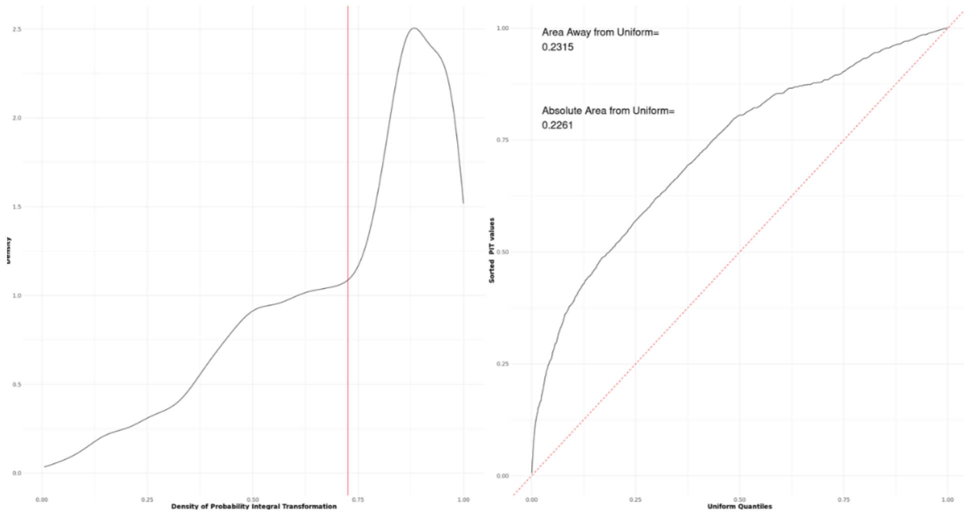
The diagnostics presented here are a direct equivalent to the incident diagnostics. These again show over dispersion in the Poisson models, there is some mis-specification/ potentially too many zeros even using the zero inflated model, though this is massively reduced as can be seen in the flatter shape of the density.



Simple Poisson Model



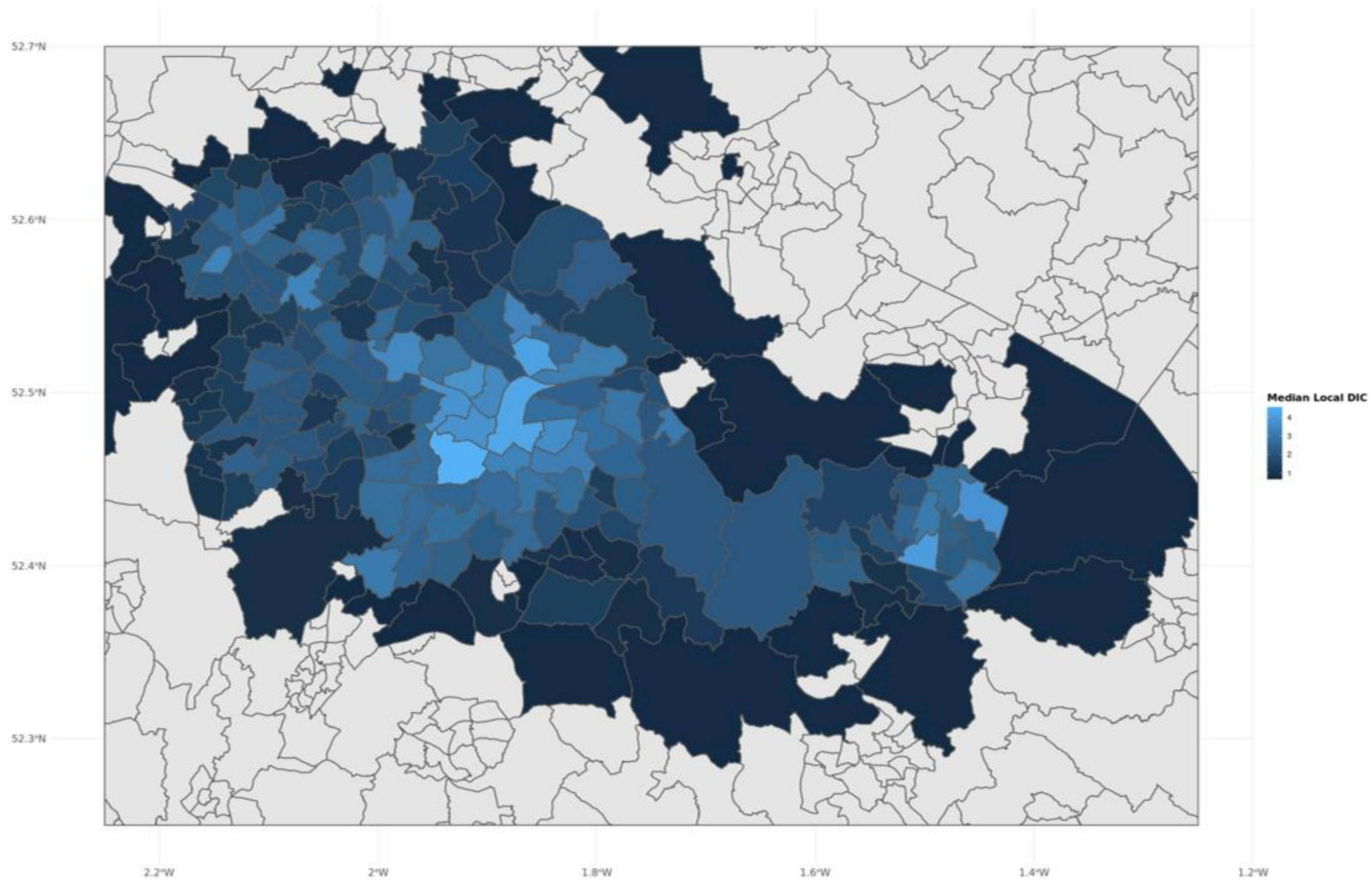
Poisson Besag Model



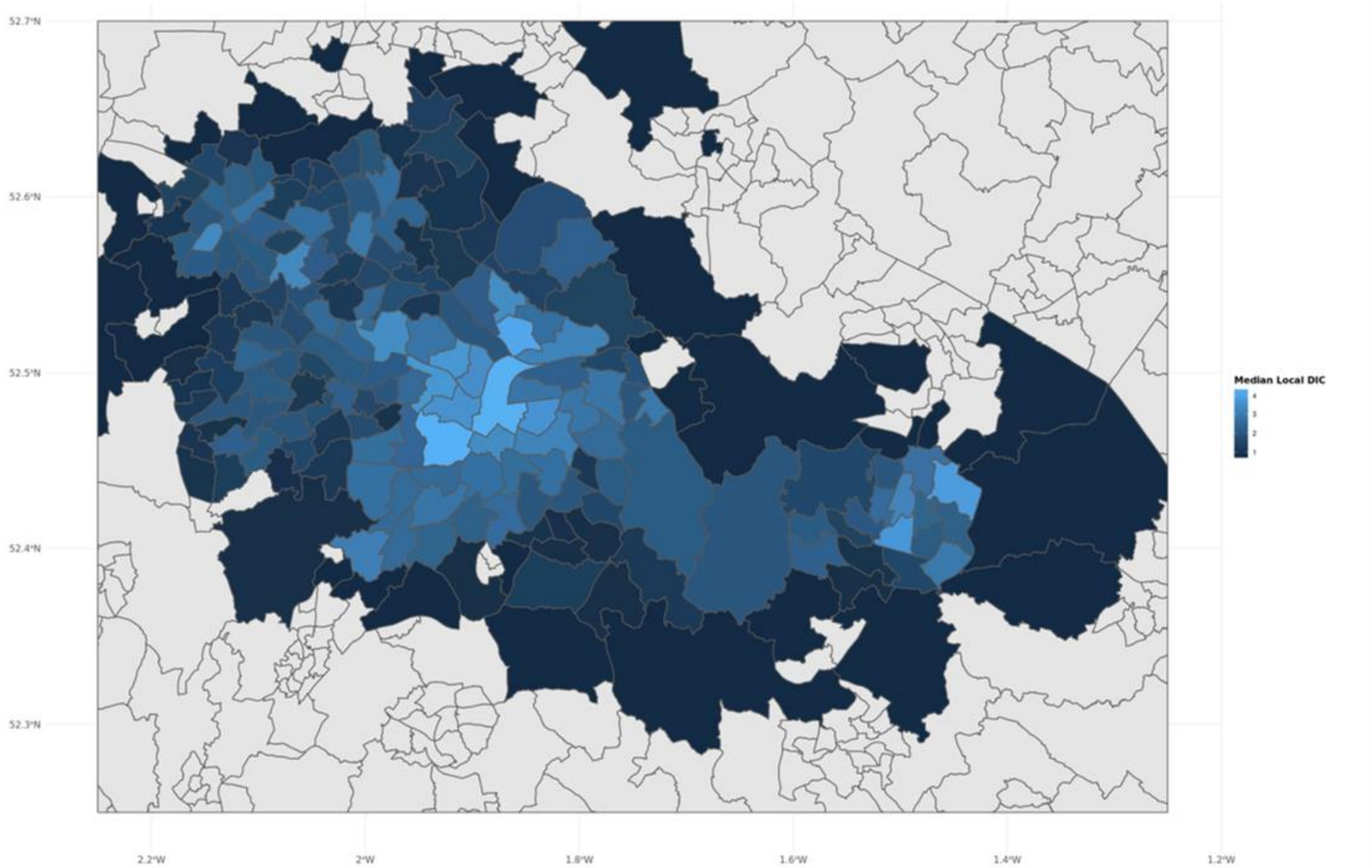
Poisson
BYM Model

Figure 44 PIT Diagnosis for Crimes Models with Poisson Models

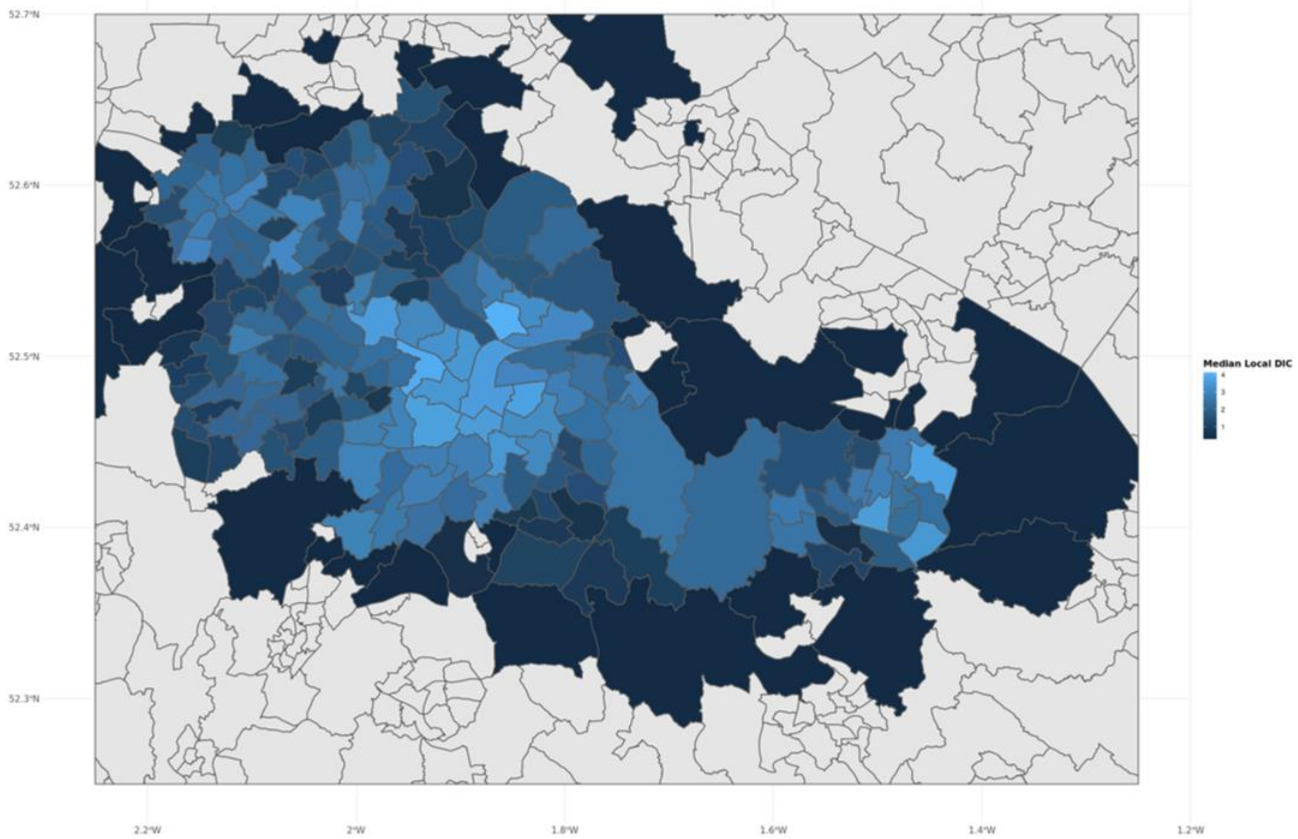
The local DICs also parallel the incident models. There are some areas that tend to be better fitted to the models than others. The BYM models show a greater spread of outcomes geographically., which would represent the actual outcomes.



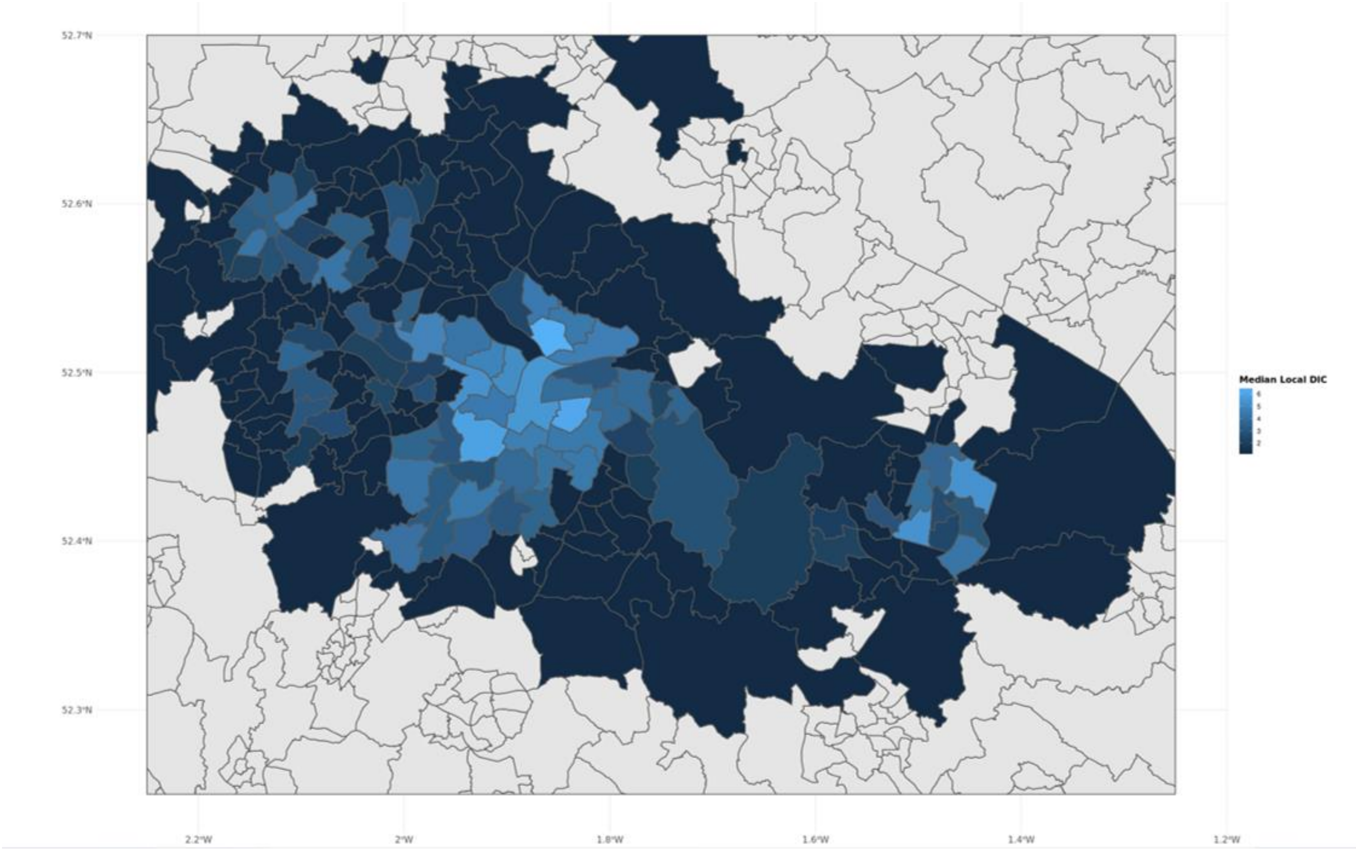
Simple Poisson Model
Local DICs



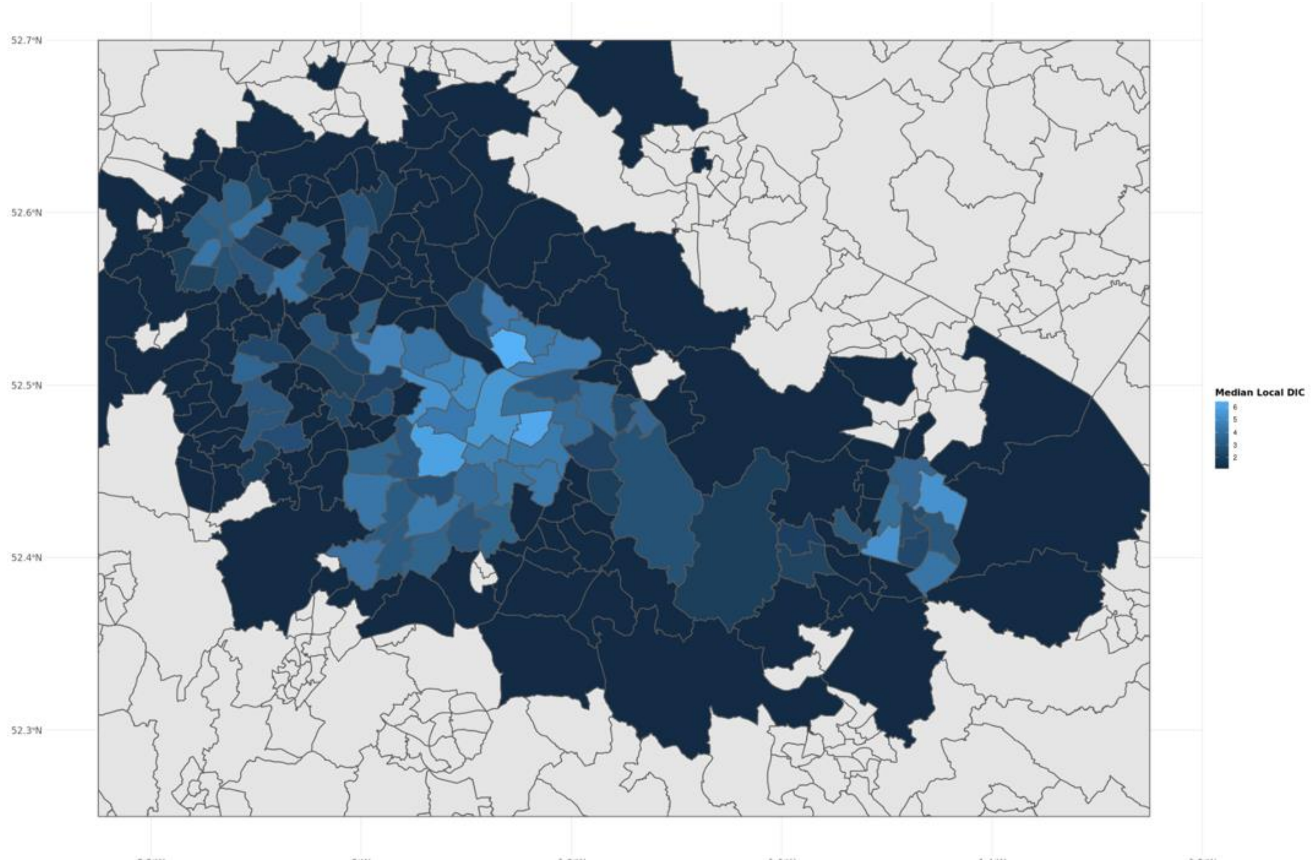
Poisson Besag Model
Local DICs



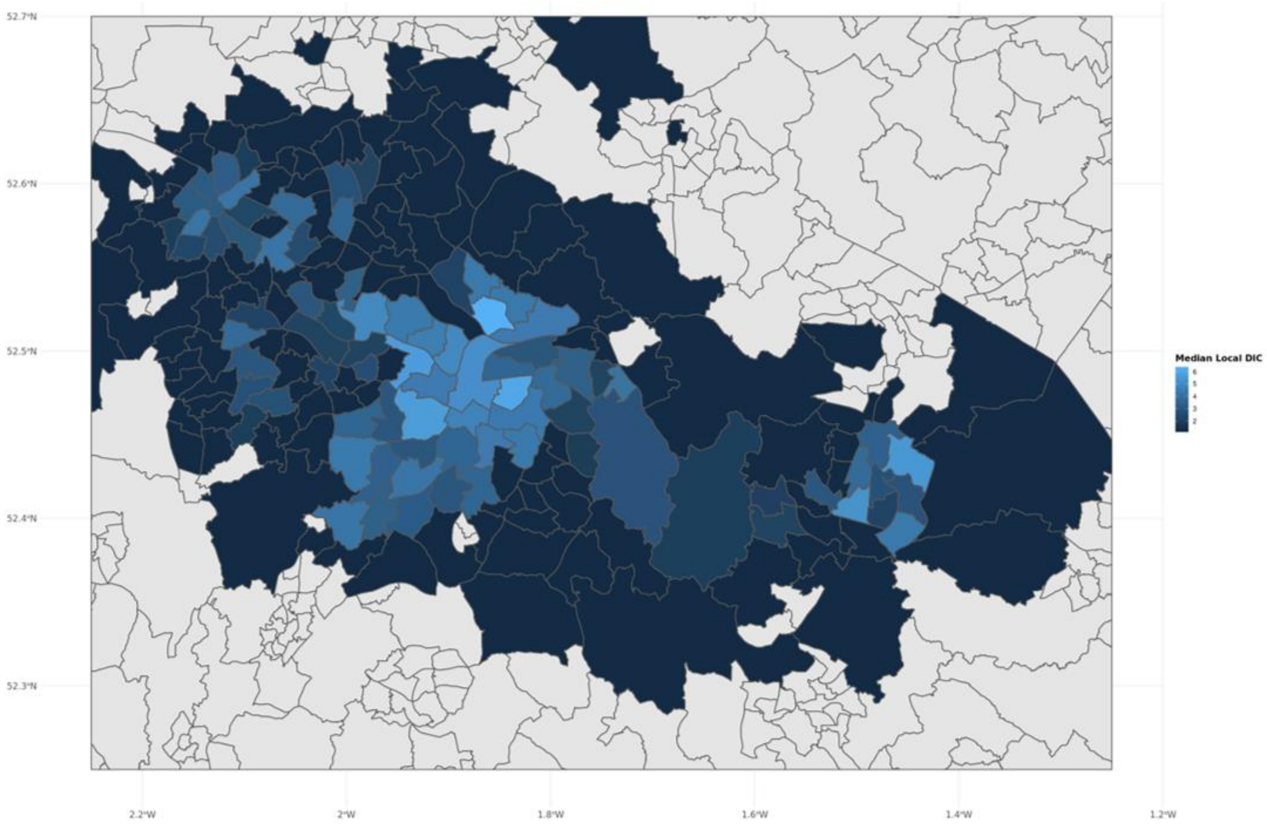
Poisson BYM Model
Local DICs



Simple Zero Inflated Negative Binomial Model Local DICs



Zero Inflated
Negative Binomial Besag
Local DICs



Zero Inflated
Negative Binomial BYM
Local DICs

Figure 45 PIT Diagnositics for Zero Inflated Negative Binomial Models of Crime

Glossary

Some commonly used terms and acronyms.

Approved Mental Health Professional (AMHP): Along with medical practioners, nurses, paramedics and occupational therapists, they can approve the use of a Section 136.

ControlWorks: The replacement for OASIS used from March 2020

COMPACT: Database recording Missing Persons cases

HMICFRS: Her Majesty's Inspectorate of Constabulary and Fire and Rescue Services. An independent body tasked with the assessment of the effectiveness and efficiency of police forces, fire & rescue services.

ICIS: Database recording Custiody information

Oasis: Database recording incidents dealt with and recorded by WMP. Retired in March 2020

Place of Safety (PoS): A location were someone detained under Section 136 can be taken. It is a locally agreed place. A police station can be used as a palce of last resort with the proviso that the person will be moved from there as soon as is possible.

Records of contact (ROC): Where WMP have received a call (or other form of contact) but where there is no need for officer attendance or investigation and so an incident record does not need to be created.

Section 135 of the Mental Health Act (S135): This allows the police to enter the home of an individual and remove them so an assessment might be carried out at a place of safety (see below). A warrant must be used to gain entry and the application for this must be made by an AMHP (see below). This will require that the individual has a mental illness and is in need of care. The maximum detention is 24 hours with a possible extension of another 12 hours. A Section 135 cannot be used to remove an individual from a public place, in this case Section 136 is used. Under Section 135 (1), the police *must* be accompanied by an AMHP and a doctor. Under Section 135 (2), the police can be unaccompanied but should try to arrange for an accompanying specialist. This subsection is often used to return individuals to hospital.

Section 136 of the Mental Health Act (S136): A section of the Mental Health Act that can be used if the police believe that a person has a mental illness and is in need of "care or control". It allows the police to take the person to a Place of Safety (see below). These are specified places including, but not limited to, homes of friends or relatives, hospitals or police stations. A mental health assessment should be carried out whilst someone is held under this Section. The maximum time under which someone can be held is 24hours, with a provision for extension of an additional 12 hours. A person *cannot* be removed from their home under Section 136, but they might be removed from communal areas such as flat corridors. There is no right of appeal to the Mental Health Tribunal.

Subject Matter Expert (SME): Local knowledgeable person from within WMP.

WMP: West Midlands Police

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[i] Information systems relating to incidents changed in March 2020. The previous system called OASIS was retired and the new system ControlWorks was put in place.

[ii] Search terms used were *mental health, triage, Section 135 or 136, 37, m/h or MHA, MCA, crisis, AMHP or Oleaster (a psychiatric ICU and place of safety),* and *'not have full capacity* '. These were checked against the information from the data and was seen to be consistent with selecting incidents where mental health issues were highlighted.

[iii] Where incidents grid references were not given and the nominal's address was available this was used.

[iv] More formally, the presence of spatial autocorrelation (and in this case also temporal correlation) can lead to the incorrect estimation of models and so poorer predictions. It should also be noted that autocorrelation carries information that is useful for predictions.