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Estimating the impact of audio-visual link on being granted bail

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AIM

The aim of this study is to estimate the causal impact of appearing via audio-visual link (AVL) on a defendants' likelihood of being granted bail.

METHOD

To estimate the impact of appearing via AVL on bail outcomes, we compare individuals who have their first court bail hearing via AVL at two New South Wales Correctional Centres, Amber Laurel and Surry Hills, between January 2018 and February 2020 with similar individuals who appear before the court in person over the same period. Three statistical approaches (logistic regression, multi-level modelling and generalised random forest) are used to adjust for the observed differences between these two groups. We present the estimated causal impact for the whole sample, along with estimates for subgroups by demographics of interest and the most serious offence committed. The credibility of the estimates hinge on two factors: 1) The extent to which we have observed and modelled the factors that influence the bail decision of the magistrate, and 2) The extent to which the allocation of AVL is 'as good as random' after controlling for all observed factors.

RESULTS

Our analysis finds no meaningful difference in the likelihood of bail refusal for defendants appearing via AVL at their first court bail hearing compared with those appearing in person. The 95% confidence intervals of our estimates range between -3.7% and 4.2%, suggesting that if any impact exists, it is a relatively small effect. We do not find any meaningful differences by demographic characteristics or offence type.

CONCLUSION

Overall, we find no evidence that appearing via AVL causes defendants to be less likely to be granted bail. However, this study does not consider all relevant costs (the experience of the defendant, procedural justice, concerns about privacy) and benefits (reduction in costs for both the state and the defendant) associated with the use of AVL.

KEYWORDS audio-visual link bail

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INTRODUCTION

Since the introduction of the *Evidence (Audio and Audio Visual Links) Act 1998 (NSW)* and the progressive installation of AVL facilities across NSW, there has been a steady increase in the use of audio-visual link to facilitate appearances at court. In NSW, AVL is used particularly intensively for bail hearings with 18,657 defendants appearing at their first court bail hearing via an audio-visual link (AVL) between January 2018 and February 2020.This accounts for nearly one-third of all first bail hearings during this period. The use of AVL by NSW Legal Aid to communicate with their clients in custody has also increased significantly, rising from approximately 20,000 AVL conferences held in 2013-2014 to approximately 28,000 in 2018-2019 (Legal Aid NSW, personal communication, September 9th, 2020). Further, the proportion of defendants appearing via AVL has rapidly increased since the advent of the COVID-19 pandemic in March 2020, with appearances in the Local and Higher courts being undertaken predominantly via AVL from the 16th and 25th of March respectively.

The implementation and widespread usage of AVL has largely been driven by logistical and efficiency concerns, rather than the experience or outcomes for the defendant. Because of this, a range of stakeholders have expressed concern that the use of this technology could be disadvantaging defendants (McKay, 2016, Wallace, 2017). Given that appearing in person is considered the default for bail hearings[1], there is a need to ensure that the use of AVL does not adversely affect the bail decision.

What is audio-visual link?

Audio-visual link is the term used to describe the video conferencing equipment that facilitates court appearances without the defendant being physically present. The AVL equipment transmits full-motion video images and audio, and can be used to share documents and other images. In a typical set-up, the defendant appears on a screen in a court, while being held in custody in a correctional centre. Barring any technical failures, the matter otherwise proceeds as if the defendant were present in person. The majority of courts and custodial facilities in NSW have AVL equipment available, allowing for defendants and witnesses to appear at court remotely.

Figure 1. An AVL setup from the perspective of the courtroom (Kashyap et. al 2018, photo provided by UTS Design Innovation Research Centre)

Figure 2. An AVL setup from the perspective of the individual in custody (Kashyap et. al 2018, photo provided by UTS Design Innovation Research Centre)

1 Evidence (Audio and Audio Visual Links) Act 1998 (NSW) pt 1A div 5B 2(a) states that the court must not direct a person to give evidence or make a submission to the court via AVL if "the court is satisfied that the evidence or submission can more conveniently be given or made in the courtroom or other place at which the court is sitting"

What has driven the usage of audio-visual link?

Appearing via AVL has a range of logistical advantages (Hatzistergos, 2008). These include:

- improved access to legal services for those in remote and/or regional areas
- matters can be dealt with more quickly and efficiently
- reduced need for transport, which reduces disruption and time spent travelling for the defendant and associated costs for the State
- improved security and safety for both the defendant and correctional/court staff.

Previous work by the NSW Bureau of Crime Statistics and Research (BOCSAR) showed that the introduction of AVL was associated with a considerable reduction in transport costs through reduced in-person court appearances (Donnelly, 2018). Examining nine courts with a new AVL facility installed in either 2015 or 2016, Donnelly (2018) reports a reduction of more than 2,200 in-person appearances which corresponds to an avoided cost of approximately $460,000 over 2 years.

In NSW, the introduction of the *COVID-19 Legislation Amendment (Emergency Measures) Act 2020* (NSW) means that the majority of court appearances now utilise AVL. Section 22C was introduced into the Evidence (Audio and Audio Visual Links) Act 1998 in response to the pandemic, and will have effect until 25th March 2021. It provides that:

- An accused person is to appear in bail proceedings by AVL unless the court orders otherwise.
- The appearance of an accused person in any physical appearance proceedings (other than proceedings relating to bail or proceedings prescribed by the regulations) may take place by way of audio visual link if the court directs.
- The appearance in any proceedings (other than proceedings prescribed by the regulations) of a witness (including a government agency witness) or legal practitioner representing a party may take place by way of audio visual link if the court directs.

Physical appearances at Local Courts were limited from 16th of March to the 1st of June 2020, with all appearances where possible conducted by AVL at time of writing (October 2020).

What determines whether you are granted bail in NSW?

The ***Bail Act 2013*** (NSW) is the key piece of legislation that determines how bail decisions are made in NSW. This Act stipulates that bail authorities must apply an 'unacceptable risk test' when making a bail determination.

Under the unacceptable risk test, bail authorities must determine if there is an unacceptable risk that the defendant, if released to bail, would:

a. fail to appear at any proceedings for the offence
b. commit a serious offence
c. endanger the safety of victims, individuals or the community, or
d. interfere with witnesses or evidence.

If one or more of these risks can be addressed with bail conditions, then the accused is to be granted conditional bail. If not, then bail is to be refused. For a small set of serious 'Show Cause' offences (e.g. offences punishable with life imprisonment, serious drug, firearm, sexual and violent offences), bail refusal is the default and defendants are required to show cause as to why bail is justified.

The Act also specifies the factors that bail authorities must consider in the bail decision. These include:

- the nature and seriousness of the offence
- the accused's criminal history
- community ties
- their pattern of compliance with previous bail conditions
- whether they have any need to be free
- whether they are young, Aboriginal, or have a cognitive impairment.

Why would AVL have an impact on bail outcomes?

There are a number of reasons why appearing via AVL may influence the outcome of bail hearings. Firstly, there is a broad literature showing that changes to the design, context and framing of a decision can influence the outcome. Social psychologists have documented a number of ways in which relatively subtle changes, such as the way in which videotaped evidence is shot (Lassiter, 2002) or the spaces in which an individual is depicted (Gosling et al., 2002), can change the way the jury perceives an individual. In the context of AVL, there is concern that the sounds of prison, the presentation of the defendant in a custodial facility (e.g. presenting in prison clothes) and the framing of defendants within the context of prison could alter how defendants are perceived (McKay, 2016). In a mock jury setting, Tait et al. (2017) show that defendants who sit in a secure dock are more likely to be convicted than those who sit next to their counsel. However, they found no difference when the defendant appeared via AVL.

Secondly, appearing via AVL may de-humanise the defendant by reducing their presence in the courtroom, thus degrading access to important aspects of the justice system. Diamond et al. (2010) observe that when videoconferencing is used, hearings become terse and rapid-fire, resulting in what they describe as a "cattle call" approach to justice. This makes it difficult for the court to give meaningful consideration to the factors relevant to bail. Wallace, Anleu and Mack (2017) report in the Australian context that many judicial officers take the view that sentencing by AVL detracts from the ability to achieve the necessary level of interaction or engagement. Yamagata and Fox (2017), in contrast, do not find any evidence that hearings are shorter for DV temporary protective orders when heard via AVL, and nor do Fielding et al (2020) in a remand court in the UK context. This suggests that consistency can largely be maintained using AVL regardless of how defendants are being heard.

Other research by McKay (2016) presents the results from interviews with defendants held at North Coast and Dilwynia correctional facilities in NSW. Some defendants reported that they found speaking during video link appearances intimidating, and the experience alienating, with those at court reacting as if the defendant had acted out of turn - further reinforcing the idea that they were not expected to speak. Kashyap et al. (2018) also report on a project to improve the experience of AVL facilities in NSW, and note that many facilities are too small, lack basic amenities such as cooling / heating and do not portray a sense of human dignity. As a result, they identify a "critical need to improve the amenity and quality of holding and waiting areas" (pp. 51), as these deficiencies degrade the experience of the defendants and create issues for correctional staff.

Thirdly, the use of AVL introduces a new set of technical issues that do not exist when the defendant appears in person. For example, defendants in the McKay (2016) study reported chronic sound issues which caused them stress, reduced their understanding of what was being said and in one case completely shut them out of proceedings due to the judge having the mute button activated for the duration of the hearing (McKay, 2016). Even when the technology is working as intended, audio can be hard to hear or distorted, the sound can come from a different location than the image of the speaker, and the sound may not be synchronised with the speaker's facial movements (Rowden et al 2013). These types of technical issues could arguably cause judicial officers to make decisions based on incomplete information, cause legal counsel to misrepresent the defendant or cause the defendant to become agitated or frustrated in a way that influences the decision.

Figure 3. Long Bay holding yard (Kashyap et. al 2018, photo provided by UTS Design Innovation Research Centre)

Finally, appearing via AVL may impact the defendants' engagement with the justice system and the resources that might be available to them. In the context of US immigration courts, Eagly (2015) found that defendants assigned to AVL were less likely to retain counsel, apply to remain lawfully in the United States, or seek an immigration benefit known as voluntary departure. Due to this decrease in engagement with the justice system, those assigned AVL were more likely to be deported despite no difference in judges' responses to claims. Thorley and Mitts (2019) replicated this study with additional data and a number of alternative specifications, and found that the core findings did not qualitatively change after the addition of the data.

McKay (2016) suggests that concerns about privacy, both due to lack of soundproofing as well as the security of the link itself, have a direct impact on defendants' relationship with their legal representatives. Some defendants reported feeling in what they could say to their legal counsel, and were concerned that prison officers were eavesdropping on their conversations.

Previous research

To date, there have been few pieces of robust quantitative research that have directly estimated the causal effect of audio-visual link on court outcomes.

Diamond et al. (2010) use an interrupted time series approach to estimate the impact that appearing via AVL had on the bond amount required for bail in Chicago, USA. They found that the average bond amount rose substantially after AVL was made the default method for bail hearings, an increase of approximately 50%. A more recent study by Fielding et al (2020) finds, conversely, that bail rates go up in cases seen in a video court when compared with observations prior to the implementation of the technology. The defendant was granted bail in 31% of hearings before the video court, compared with 39% of hearings after implementation.

The study by Eagly (2015) (and the later replication by Thorley and Mitts (2019)) referred to above presents mixed evidence for AVL impacting defendant outcomes. They find that defendants assigned to AVL were more likely to be deported, but judges did not deny respondents' claims in AVL cases at higher rates. Instead, this "outcome paradox" was driven by lower rates of engagement with the justice system (defendants less likely to apply to remain or seek immigration benefits).

The current study

The aim of this study is to estimate the causal effect of appearing via AVL on defendants' likelihood of being granted bail, when compared with those that appeared in person. For this study, estimates of the causal impact are presented in aggregate along with estimates of the causal impact for subgroups defined by the following offender characteristics:

- gender
- Aboriginality
- SEIFA quartile[2]
- remoteness area[3]
- most serious offence (16 most common)

These subgroup analyses are presented for two (overlapping) reasons:

1. The causal effect of appearing via AVL may differ significantly by the type of offence and/or by defendant characteristics. We have selected a subset of characteristics that we believe would be most salient in first bail decisions;
2. In our sample, there is significant imbalance between those appearing via AVL and those appearing in person in three of these characteristics (More likely to be seen in person for those identified as Aboriginal, in major cities and higher SEIFA quartile). These differences are largely driven by the way in which AVL has been implemented in NSW. Although these factors have been accounted for in the analyses using statistical methods, estimates by characteristic makes it clear how (or if) the characteristic interacts with the outcome.

METHOD

Data source

To estimate the impact of appearing via AVL on bail outcomes, we have created a dataset that combines:

- Data for each bail hearing, including whether the defendant appeared via AVL and the outcome of the hearing. This data was provided to the Bureau of Crime Statistics and Research (BOCSAR) by Corrections Research Evaluation and Statistics (CRES) unit within Corrective Services NSW;
- Data on offending history, demographics and characteristics of the offence that was the subject of the bail hearing. This data has been extracted from the BOCSAR Reoffending Database (ROD).

These two datasets have been linked using the Master Index Number (MIN)[4] and the first bail date. The combination of the CRES and ROD data allows us to construct a dataset where each row is a unique first bail hearing containing crucial information on whether the defendant appeared via AVL and the bail outcome, as well as a rich set of data on individual-level characteristics.

2 Socio-Economic Indexes for Areas (SEIFA) is a product developed by the ABS that ranks areas in Australia according to relative socio-economic advantage and disadvantage.
3 Remoteness Areas divide Australia into 5 classes of remoteness on the basis of a measure of relative access to services.
4 This is a unique identifier assigned by Corrective Services NSW

Sample

The sample for this study includes all first bail hearings in NSW from January 2018 to February 2020. Each row of the data corresponds to the first bail hearing for a set of charges for an individual. This means that an individual can appear multiple times in the dataset, but each time for a separate set of charges.

We have further limited our analysis to:

- **Hearings for defendants refused bail by Police**: Those who are granted bail by police cannot appear via AVL for their first bail hearing. We have thus restricted our analysis to those who have been police bail refused to keep the comparison group as similar as possible to those appearing via AVL;
- **Defendants who have appeared via AVL from Surry Hills or Amber Laurel Correctional Centre, or those that did not appear via AVL**: The vast majority (95%+) of hearings via AVL in our dataset are conducted from either Surry Hills or Amber Laurel Correctional Centre. We have restricted our analysis to these observations, as the small sample size from the other facilities make it difficult to distinguish any features specific to the facility from other factors that influence the bail outcome.
- **Defendants who are older than 18**: We exclude eight observations of defendants that were under 18 in our dataset, so we can concentrate our analysis on adult defendants.

This leaves us with 25,926 hearings across 18,653 unique defendants for the analysis.

Empirical approach

In order to credibly estimate the impact of appearing via AVL, we need to isolate the impact of appearing via AVL from all possible confounding factors that could influence the bail outcome. In the absence of explicit randomisation, our approach is to exploit the fact that in NSW defendants are allocated to appear via AVL only if they arrive at the correctional facility between 2:30pm and 5:00am. This in turn depends on when they are arrested, and how long it takes to process the defendant.

This creates the conditions for a natural experiment since group allocation can be considered plausibly independent from bail outcomes after conditioning on observable characteristics of the case and the defendant.

Below, we briefly describe the bail process and how the use of AVL is determined.

The bail process

1. First, a defendant is charged with one or more offences by police. This process takes 4-6 hours depending on the complexity of the case and the condition of the defendant (e.g. if they are intoxicated or otherwise impaired and unable to answer questions) when arrested.
2. The police then make a decision on whether to release the defendant to bail until their court matter is heard ("The Police Bail Decision").
3. If police refuse bail, then the accused is held on remand, typically for a period of 24 hours or less, until they can be brought before a magistrate for their first court bail hearing.
4. The facility where a defendant is held on remand is determined by their location, time of arrest and time taken to charge. These factors in turn determine whether they appear via AVL or in person for their bail hearing.
5. If a defendant is held on remand at Amber Laurel or Surry Hills Correctional Centre and arrive between 2:30pm and 5:00am, they would appear via AVL.
6. The magistrate then decides whether or not to overturn the police decision and grant bail, or continue to remand the defendant in custody ("The First Court Bail Decision").

It is important to note that the NSW Police Force and Corrective Services NSW have no influence over who appears via AVL. The use of AVL is determined entirely by location, time of arrest, time taken to charge and the factors that determine these variables.

We compare those who have appeared via AVL at Amber Laurel and Surry Hills Correctional Centres with those that appear at court in person, using a number of statistical methods to adjust for the observed differences between these two groups. Our empirical approach hinges on the extent to which the use of AVL for first bail hearings is unrelated to bail outcomes after controlling for all observed factors in our dataset. We do not observe the time of arrest, so we are unable to test directly whether this assumption is reasonable for this analysis. If there are unobserved characteristics that determine both the bail decision and the time of arrest these may introduce significant bias.

Statistical analysis

As a large number of factors influence the bail decision, our statistical model needs to include a large number of predictors to isolate the influence of appearing via AVL from other factors. Estimating a statistical model with a large number of predictors using traditional approaches (such as single regression inclusive of all predictors) can be challenging, particularly when there is imbalance on some of the independent variables. In particular, in our study, there are a large number of judicial officers and Police Area Commands (PACs) in the dataset that are important to control for and are likely to differ significantly in frequency between those appearing via AVL and those appearing in person.

For each section, we present estimates of the causal effect using three different approaches:

1. Logistic regression

First we present estimates from a logistic regression including controls for each of the predictors detailed below, except judicial officer and Police Area Command.

For this approach, we estimate the following model:

$$\text{Bail}_i = \text{AVL}_i + \text{Offence characteristics}_i + \text{Hearing characteristics}_i + \text{Prior offending}_i + \text{Demographics}_i + \epsilon_i$$

Estimates from this approach will be unreliable if the impact of the judicial officer or Police Area Command differs significantly for those appearing via AVL and those appearing in person, as we are unable to control for these factors. All estimates are presented as average marginal effects.

2. Multi-level model

Second, we present estimates from a multi-level model, which estimates the impact of judicial officer, the Police Area Command, and the offence type by partially pooling the estimates (e.g. by constraining the parameters to a normal distribution). These are sometimes referred to as “random effects”.

For this approach, we estimate the following model:

$$\text{Bail}_i = \text{AVL}_i + \text{Offence characteristics}_i + \text{Hearing characteristics}_i + \text{Prior offending}_i + \text{Demographics}_i + \text{Judicial officer}_i + \text{Police Area Command}_i + \epsilon_i$$

The crucial assumption for this analysis is that for any given group, we would expect the impact of the group to be uncorrelated with the impact of appearing via AVL. This allows us to include all the predictors of interest, with estimates of their impact being “pooled” towards the average parameter value within the group, weighted by the number of observations in each group.

These have been estimated using restricted maximum likelihood where possible, and where these models do not converge, estimated using Markov chain Monte Carlo with weakly informative priors.

3. Generalised random forest

Finally, we estimate the causal effect using a generalised random forest. Random forest methods are particularly useful in settings where there are a large number of predictors, as they are able to flexibly adapt to different functional forms in a stable and are easy to implement.

We estimate an "honest" causal tree method detailed in Athey, Tibshirani and Wager (2018), which adapts this method to produce estimates of the conditional mean which are analogous to estimates produced from regression models. This method uses half the data in any subset to estimate which predictor has the largest difference in treatment effect, and then the other half to estimate the magnitude of the effect. We implement this technique using the same data and set of covariates as used in the multi-level model.

The purpose of providing three estimates of each causal effect is to allow the reader to understand the range of estimates that are consistent with the data. All three approaches are reasonable, and have their relative advantages. The intention is to demonstrate that the conclusions drawn from the analysis are robust to the estimating approach, even if there is variation in the estimate from each approach.

Estimating the causal impact of AVL for subgroups of interest

As mentioned above we also estimate the causal impact of AVL for a number of subgroups. Specifically, we present estimates by gender, Aboriginality, SEIFA quartile, remoteness of area and the most serious offence considered at the bail hearing.[5] The offences have been categorised using the Australian and New Zealand Standard Offence Classification (ANZSOC) (ABS, 2011).

These subgroup estimates have been estimated for two reasons:

1. It is possible that the causal impact of AVL depends critically on how the defendant is perceived or the discretion available to the magistrate. If this is the case, then we may see large disparities in the causal impact of AVL based on salient demographic or offence characteristics, despite observing small differences in aggregate.
2. As noted in the descriptive statistics section below, there is a significant demographic imbalance between those that appear via AVL and those that appear in person. This is true for Aboriginality, SEIFA quartile and remoteness of area, and is largely driven by how AVL has been implemented in NSW. These analyses help to understand how much these imbalances have driven the aggregate results by looking at the estimate of the causal impact of AVL within each subgroup.

As with the aggregate results, we present estimates from three analogous approaches to estimation:

1. A logistic regression using only data from the corresponding group (e.g. a "split" regression model);
2. An estimate from a multi-level model where AVL is interacted with the demographic characteristic (e.g. as a fixed effect) or included as a predictor for the offence group (e.g. as a random effect);
3. An estimate from a generalised random forest, where the estimated causal impact of AVL is estimated as a conditional average treatment effect.

These models continue to include all predictors in the model (e.g. offence characteristics, hearing characteristics, prior offending history, demographic variables) as in the previous analysis, in order to estimate the causal impact of AVL for each of the demographic sub-groups.

It is worth noting that we have not corrected for multiple hypothesis testing in any of our analyses. In particular, the estimates from the split regression model are likely to suffer from unreasonably narrow confidence intervals and Type 1 errors if considered at face value. However, given the features of the multi-level model (which pools estimates towards the group mean) and the generalised random forest (which uses a hold-out set to estimate the causal effect), this is not a major concern for these two

5 Offences have been ordered in seriousness using the Median Sentence Ranking as developed by MacKinnell, Poletti & Holmes (2010)

approaches. Thus, we have included the estimates from the split model as an intuitive baseline for the other estimates, but would not consider these estimates as robust as the estimates from the other two approaches (Athey, Tibshirani, & Wager, 2018; Gelman, Hill, & Yajima, 2012).

Variables

There is one outcome variable for this study:

- **Granted bail:** This variable is TRUE if the defendant was granted bail at the bail hearing, and FALSE otherwise.

There are a large set of predictors included in this analysis:

Offence characteristics

- **Most serious offence**: A categorical variable with 96 possible values, one for each of the ANZSOC groups that were the most serious offence for that hearing in this dataset (out of a total 183 offences defined in the ANZSOC).
- **Median sentence ranking of most serious offence**: We use the median sentence ranking as developed by MacKinnell et al. (2010) to determine the most serious offence, and use this ranking as a continuous predictor of the bail outcome.
- **Number of offences**: A positive integer indicating the total number of offences considered for the hearing.
- **Whether the offence was an indictable offence**: TRUE if the offence was indictable, FALSE otherwise.
- **Whether the offence was a show cause offence**: TRUE if the offence was a 'Show Cause' offence[6], FALSE otherwise.
- **Police Area Command that made the arrest**: A categorical variable with 60 possible values for each of the police areas that are represented in the data.

Hearing characteristics

- **Whether the hearing was on a weekend**: TRUE if the hearing was held on a weekend, FALSE otherwise.
- **The judicial officer associated with the bail hearing**: A categorical variable with 310 possible values, one for each of the judicial officers that have an ID in the data.

Prior offending history (two years before hearing)

For these definitions, we have used the division as described in the Australian and New Zealand Standard Offence Classification 2011 (ANZSOC)

- **Violent crime**: Number of offences committed in ANZSOC division 1, 2, 3, 5, 6.
- **Property**: Number of offences committed in ANZSOC division 7, 8, 9, 12.
- **Drug**: Number of offences committed in ANZSOC division 10.
- **Traffic**: Number of offences committed in ANZSOC division 14.
- **Other**: Number of offences committed in ANZSOC division 4, 11, 13, 16.
- **Prison sentence**: TRUE if they had previously been given a prison sentence, FALSE otherwise.

6 Show Cause offences refer to serious offences (e.g., homicide and rape). A complete list of Show Cause offences is available for interested readers under Section 16B of the Bail Act 2013 (NSW).

Demographic variables

- **Gender**: This variable is recorded as a binary variable, “Male” or “Female”.
- **Age category**: This variable is recorded as a numeric variable and is the individual’s age at the time of the hearing in years. We have then converted this to a categorical variable with 6 possible values (“18-24”, “25-34”, “35-44”, “45-54”, “55-64”, “65+”).
- **Aboriginality**: This variable is recorded as a categorical value with three possible values, Aboriginal, Non-Aboriginal or Unknown, and is constructed from whether an individual has ever identified themselves as Aboriginal to police in our data.
- **SEIFA quartile**: A categorical variable with five values, one for each quartile of the distribution and one for missing values.
- **Remoteness**: A categorical variable indicating whether the defendant’s place of residence is in a Major City, Inner regional, Outer regional or Remote/Very remote area or missing (ABS 2016).

Descriptive statistics

Below we present unadjusted averages and proportions for each of the predictors included in the analysis. For numeric variables, we present the average and the standard deviation. For categorical variables, we present the total number in each category along with the corresponding proportion of the group.

Table 1. Summary statistics by appearance type

	Appear in person (N = 17903)	Appear via AVL (N = 8023)	*p*-value
Granted bail			< 0.01
TRUE	9900 (55%)	4166 (52%)	
FALSE	8003 (45%)	3857 (48%)	
'Show cause' offence			0.09
TRUE	17573 (98%)	7899 (98%)	
FALSE	330 (2%)	124 (2%)	
Gender			< 0.01
Female	2505 (14%)	1246 (16%)	
Male	15398 (86%)	6777 (84%)	
Age (at appearance)			< 0.01
18-24	3091 (17%)	1264 (16%)	
25-34	6097 (34%)	2581 (32%)	
35-44	4953 (28%)	2378 (30%)	
45-54	2548 (14%)	1366 (17%)	
55-64	536 (3%)	291 (4%)	
65+	125 (1%)	49 (1%)	
Not recorded	553 (3%)	94 (1%)	
Aboriginality			< 0.01
Aboriginal	7341 (41%)	2598 (32%)	
Non-Aboriginal	10515 (59%)	5381 (67%)	
Unknown	47 (0%)	44 (1%)	
SEIFA quartile			< 0.01
1 (most disadvantaged)	4918 (28%)	1648 (21%)	
2	7965 (45%)	2219 (28%)	
3	3998 (23%)	3029 (38%)	
4 (least disadvantaged)	768 (4%)	1029 (13%)	
Not recorded	254	98	
Remoteness area			< 0.01
Not recorded	253	98	
Inner regional	5033 (29%)	375 (5%)	
Major cities	10729 (61%)	7429 (94%)	
Remote	1888 (11%)	121 (2%)	
Prior violent offences (previous 2 years)			0.02
Mean (SD)	0.7 (1.3)	0.7 (1.2)	
Range	0.0 - 17.0	0.0 - 16.0	
Prior prison sentence (previous 2 years)			0.23
Mean (SD)	0.4 (0.8)	0.5 (0.9)	
Range	0.0 - 7.0	0.0 - 8.0	

Summary statistics for all other variables are provided in Table A1 of the Appendix.

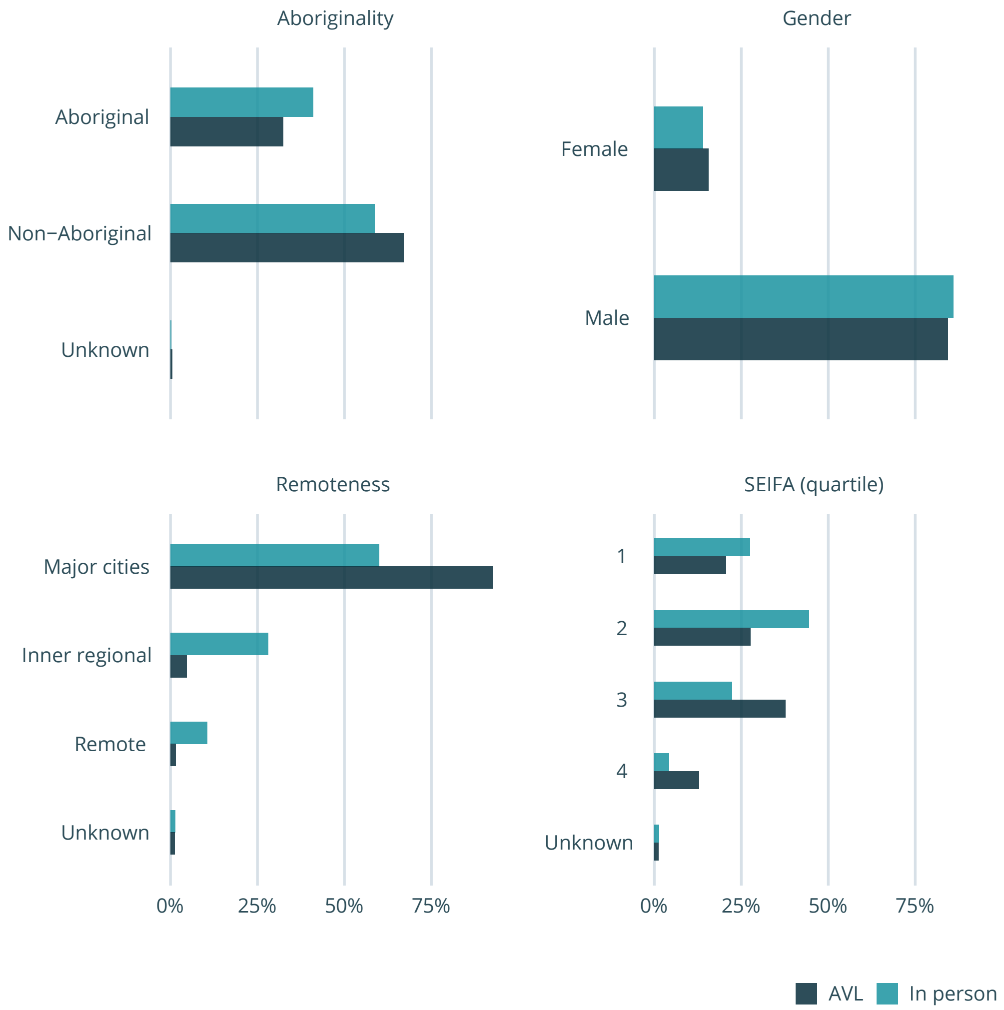
There is a meaningful imbalance between the two groups on three predictor variables:

- 41% of first bail appearances in person involve an Aboriginal defendant (compared with 32% via AVL);
- 27% of first bail appearances in person involve a defendant from an area in the top two quartiles of the SEIFA index (compared with 51% for via AVL);

- 61% of first bail appearances in person involve a defendant from a major city (compared with the vast majority (94%) of those that appear via AVL).

These difference are shown graphically in Figure 4 below.

Figure 4. Sample balance (AVL vs In Person appearance)



We present results split by each of these categories (e.g. comparing just Aboriginal defendants who appeared in person against those who appeared via AVL) to investigate whether the causal effect of AVL differs meaningfully between groups.

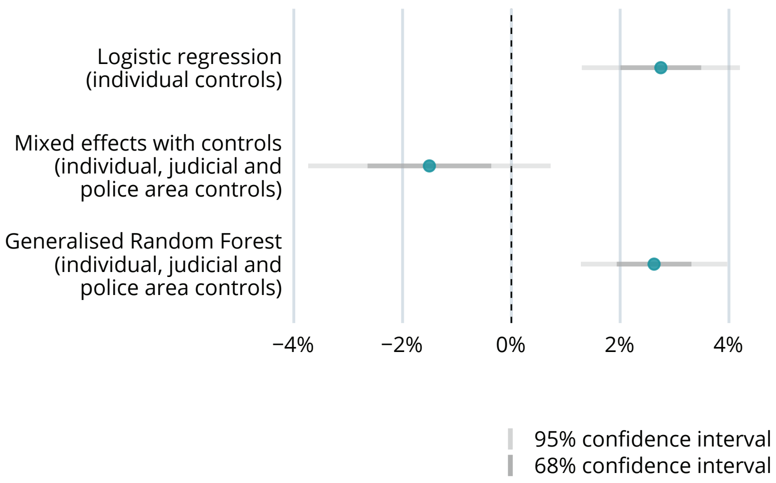
RESULTS

For this analysis, we investigate whether the bail outcome at a first bail hearing is impacted by an individual appearing via AVL versus in person (i.e. the "causal impact of AVL").

Aggregate impact

First, we investigate the average causal impact of AVL across all observations in the data. The estimates are presented graphically below. The plot shows the point estimate for the average causal impact, with the dark shaded area indicating the 68% confidence interval (e.g. 1 standard error), and the lighter area showing the 95% confidence interval. An increased rate of bail for those appearing via AVL is shown by the point being further to the right of the plot, while a decreased rate of bail is shown by the point being further to the left of the plot (with no impact represented by the dotted line). All points within the shaded area for each estimate are consistent with the model at the 95% level of confidence.

Figure 5. Average causal impact of AVL, full sample



Together the results from the three different approaches suggest that there is no meaningful negative effect of AVL on bail outcomes in aggregate. The estimated causal impact of AVL ranges from a 1.5% reduction in the likelihood of bail (estimated using a multi-level model) to a 2.7% increase (from the split regression). Based on the 95% confidence intervals both the estimate from the split regressions and the generalised random forest, indicate an advantage for defendants appearing via AVL of between 1.3% and 4.2%.The lower bound of the 95% confidence interval is a 3.7% reduction in bail, making it the largest negative effect consistent with one of our estimates (mixed effects with controls), but this is comparable to the largest positive effect within a 95% confidence interval.

Table 2. Average causal impact of AVL on the probability of being granted bail

	Logistic regression	Multi-level model	Generalised random forest
Estimate	2.7%	-1.5%	2.6%
	(0.7%)	(1.1%)	(0.7%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	Yes	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	Yes	Yes	Yes

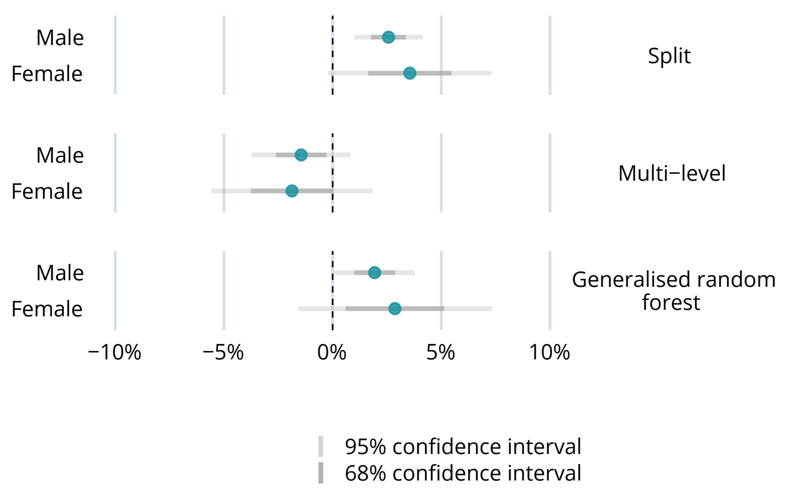
Impact by demographics and most serious offence

Below, we estimate the causal impact of AVL separately by gender, Aboriginality, SEIFA quartile, remoteness of area and most serious offence. As would be expected, the estimates split by these demographic groups are centered around the estimate of the aggregate impact for each of the modelling approaches. Therefore, in this section our focus is on the difference in the causal impact of AVL between groups rather than the estimated causal impact of AVL for each group.

Gender

Regardless of the estimation approach, we see very similar estimates of the causal impact of AVL on bail decisions for both males and females.

Figure 6. Average causal impact of AVL, by Gender



The largest difference is from the generalised random forest, which estimates that females are 2.5% more likely to receive bail if they appear via AVL than if they appear in person. This compares with males who are estimated to be 1.8% more likely to receive bail if appearing via AVL than if appearing in person (a difference of 1.7%).

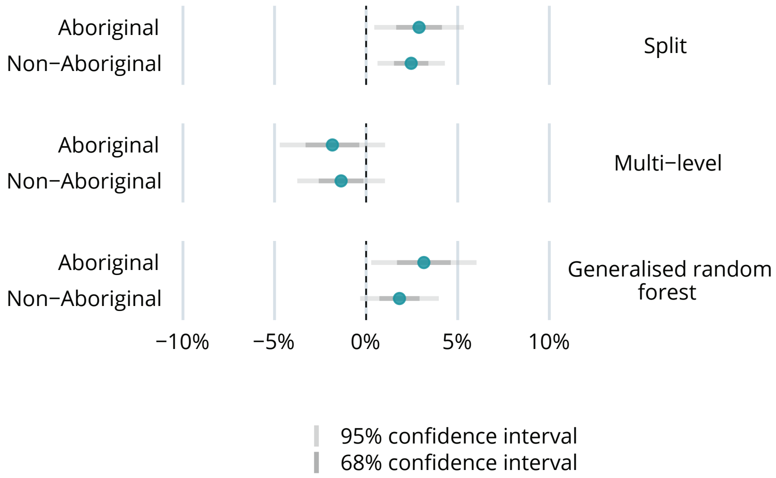
Table 3. Average causal impact of AVL on the probability of being granted bail, by gender

	Logistic regression	Multi-level model	Generalised random forest
Female	3.6%	-1.9%	2.7%
	(1.9%)	(1.9%)	(2.3%)
Male	2.6%	-1.4%	1.9%
	(0.8%)	(1.2%)	(0.9%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	At offence level	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	Yes	Yes	Yes

Aboriginality

We also do not see any meaningful differences in the impact of appearing via AVL on bail outcomes between those identified as Aboriginal and those identified as Non-Aboriginal. This result is robust across the three methods.

Figure 7. Average causal impact of AVL, by Aborignality



As with the results by gender, the largest difference in the estimated causal impact of AVL is from the generalised random forest, which estimates a 3.4% increase in the likelihood of bail for defendants identified as Aboriginal, compared with a 1.9% increase for defendants identified as Non-Aboriginal (a difference of 1.5%).

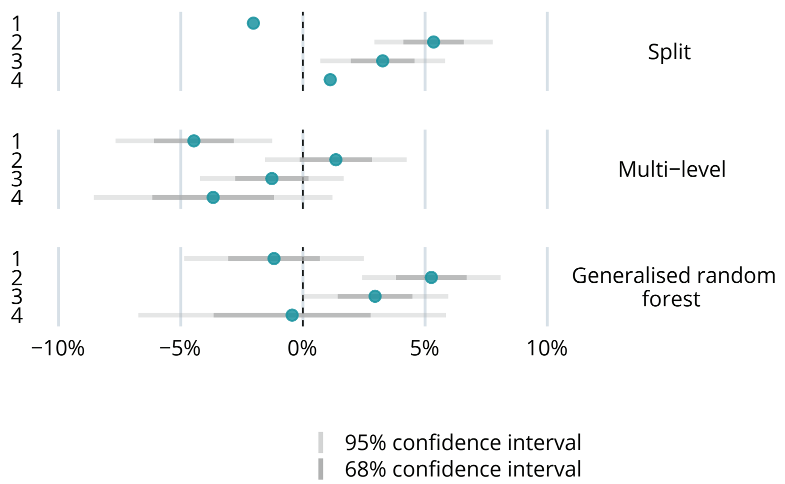
Table 4. Average causal impact of AVL on the probability of being granted bail, by Aboriginality

	Logistic regression	Multi-level model	Generalised random forest
Aboriginal	2.9%	-1.8%	3.2%
	(1.2%)	(1.5%)	(1.5%)
Non-Aboriginal	2.5%	-1.4%	1.8%
	(0.9%)	(1.2%)	(1.1%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	Yes	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	Yes	Yes	Yes

SEIFA quartile

The estimated causal impact of AVL is higher for those in the middle two quartiles of the SEIFA distribution, and this is robust to the statistical model used.

Figure 8. Average causal impact of AVL, by SEIFA quartile



Using a split regression approach, we estimate that defendants in the second and third SEIFA quartiles are approximately 5% and 3% more likely to receive bail if they appear via AVL respectively. Across models, we estimate that those in the second SEIFA quartile are roughly 5% more likely to be granted bail when appearing via AVL compared to those in either the highest or lowest SEIFA quartiles. We estimate the effect on bail is similar for the highest and lowest quartiles, they are both 3.7% to 4.5% less likely to be granted bail as estimated by the multi-level model, or 0.4% to 1.1% less likely to be granted bail as estimated by the generalised random forest model.

This suggests that any negative impacts due to appearing via AVL are concentrated at the extreme ends of the SEIFA distribution.

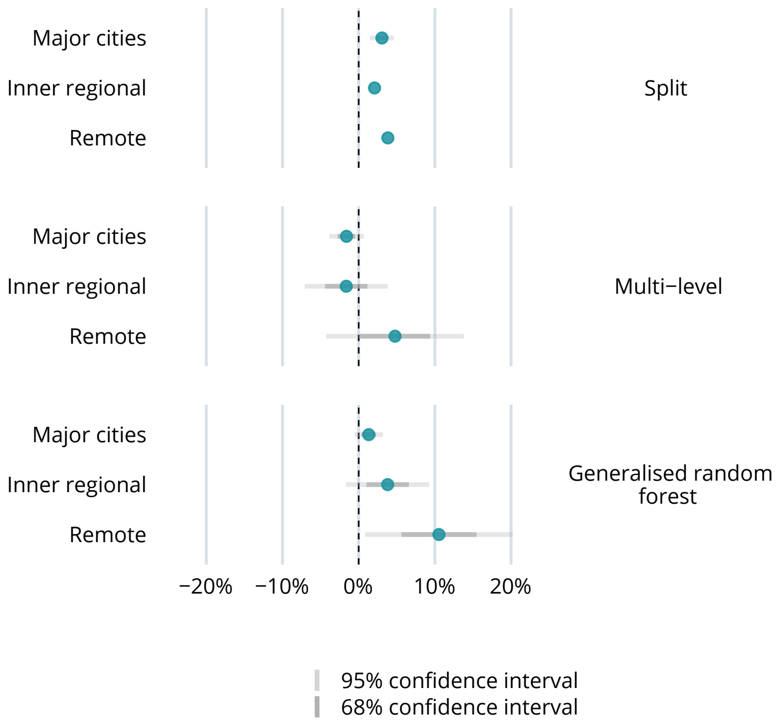
Table 5. Average causal impact of AVL on the probability of being granted bail, by SEIFA quartile

	Logistic regression	Multi-level model	Generalised random forest
1 (most disadvantaged quartile)	-2.0%	-4.5%	-1.1%
	Could not estimate	(1.6%)	(1.9%)
2	5.3%	1.3%	5.2%
	(1.2%)	(1.5%)	(1.4%)
3	3.3%	-1.3%	3.0%
	(1.3%)	(1.5%)	(1.5%)
4 (least disadvantaged quartile)	1.1%	-3.7%	-0.4%
	Could not estimate	(2.5%)	(3.2%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	Yes	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	Yes	Yes	Yes

Remoteness of area

The estimated causal impact of AVL is larger for those in remote areas, but this estimate is noisy and unreliable due to the small number of individuals appearing via AVL from these regions.

Figure 9. Average causal impact of AVL, by Remoteness of area



We estimate that defendants from remote areas were 3.8% - 10.9% more likely to receive bail when appearing via AVL. However, there is a lot of uncertainty around this estimate due to our sample containing only 29 defendants from remote areas who appeared via AVL at their first bail hearing, compared with 360 defendants from remote areas who appeared in person. As a result, the 95% confidence interval for this estimate is implausibly large, ranging from a decrease in the probability of being granted bail of 15% to an increase of 31%.

Table 6. Average causal impact of AVL on the probability of being granted bail, by remoteness area

	Logistic regression	Multi-level model	Generalised random forest
Major cities	3.1%	-1.7%	1.4%
	(0.8%)	(1.2%)	(0.9%)
Inner regional	2.1%	-2.0%	3.8%
	Could not estimate	(2.8%)	(2.8%)
Remote	3.8%	4.5%	10.9%
	Could not estimate	(4.6%)	(4.9%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	Yes	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	Yes	Yes	Yes

In contrast, the estimated causal impact of AVL for defendants from inner regional and major cities is consistent with the aggregate estimates, with no meaningful differences between the estimate for defendants from major cities and inner regional areas.

Most serious offence

Finally, we estimate the causal impact of AVL by the most serious offence that the defendant has been charged with. We have restricted the estimates to the 16 most common offences that were the 'most serious offence' for the respective bail hearing. This captures approximately 80% of all hearings included in our sample.

For the majority of offences, there are few meaningful differences in the causal impact of AVL by offence type. For one offence, property damage, we see multiple models that estimate a meaningfully different effect. However, the estimated causal impact of AVL for this offence is positive, suggesting that appearing via AVL is increasing the probability of bail.

Figure 10. Average causal impact of AVL, by most serious offence

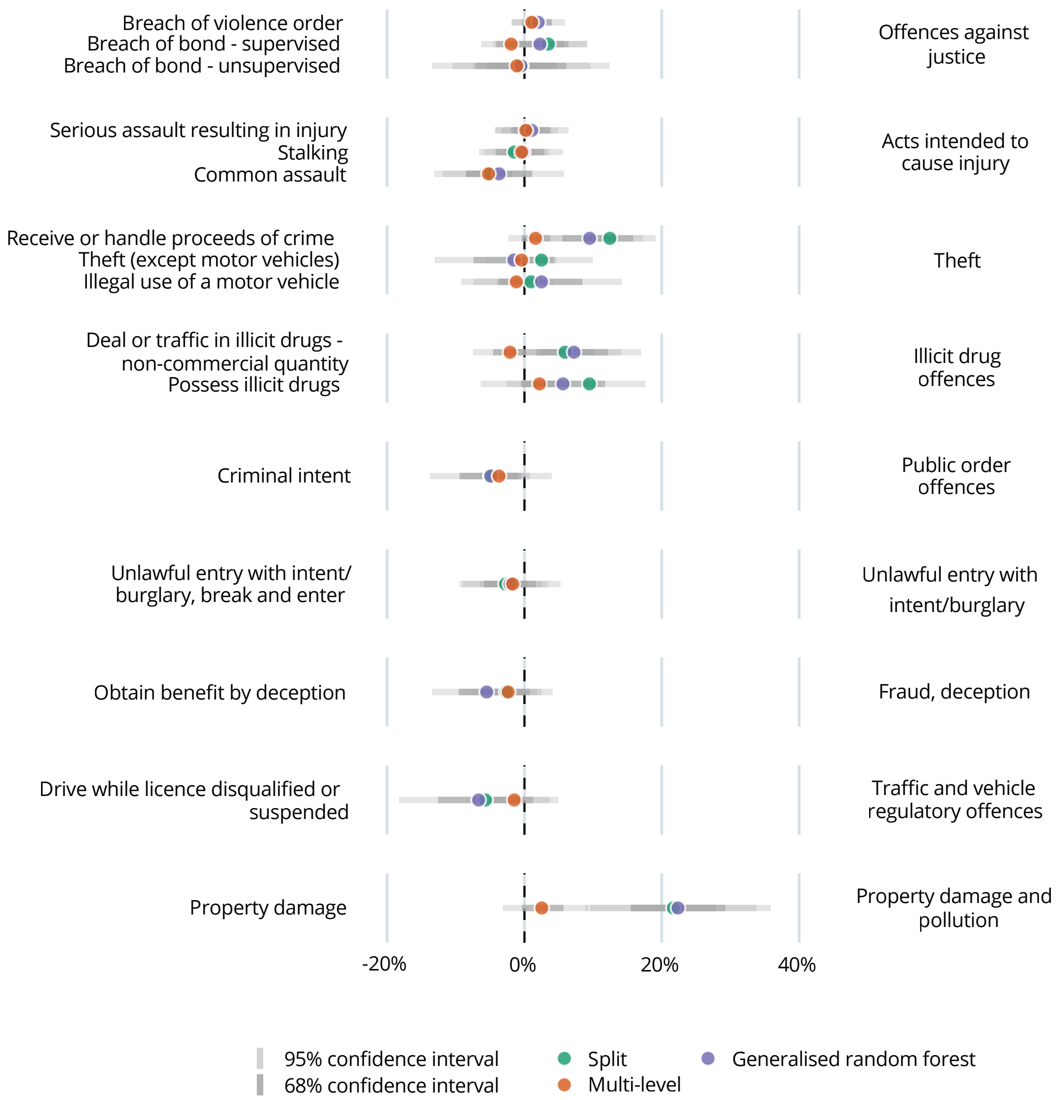


Table 7. Average causal impact of AVL on the probability of being granted bail, by offence type

	Estimated causal impact of AVL on the probability of being granted bail		
	Logistic regression	Multi-level model	Generalised random forest
Breach of violence order	0.7%	1.1%	2.0%
	(1.6%)	(1.4%)	(2.0%)
Serious assault resulting in injury	0.7%	0.2%	1.1%
	(2.1%)	(1.7%)	(2.8%)
Stalking	-1.2%	-0.4%	-0.2%
	(2.4%)	(1.8%)	(2.9%)
Breach of bond - supervised	-2.0%	-1.9%	2.1%
	(2.7%)	(2.2%)	(3.5%)
Unlawful entry with intent/burglary, break and enter	-3.5%	-1.7%	-2.1%
	(3.0%)	(2.3%)	(3.8%)
Receive or handle proceeds of crime	9.1%	1.6%	9.6%
	(3.2%)	(2.1%)	(4.0%)
Obtain benefit by deception	-3.6%	-2.4%	-5.6%
	(3.2%)	(2.4%)	(4.1%)
Criminal intent	-7.0%	-3.8%	-5.0%
		(2.9%)	(4.5%)
Deal or traffic in illicit drugs - non-commercial quantity	4.1%	-2.1%	7.2%
	(3.9%)	(2.4%)	(5.0%)
Common assault	-6.1%	-5.3%	-3.8%
	(3.8%)	(3.4%)	(4.8%)
Possess illicit drugs	11.9%	2.1%	5.6%
	(4.5%)	(2.5%)	(6.1%)
Drive while licence disqualified or suspended	-7.6%	-1.5%	-6.6%
		(2.7%)	(5.9%)
Theft (except motor vehicles)	4.0%	-0.4%	-1.8%
		(2.4%)	(5.9%)
Breach of bond - unsupervised	-2.1%	-1.1%	-0.9%
	(4.9%)	(3.2%)	(6.6%)
Illegal use of a motor vehicle	-0.8%	-1.3%	2.8%
		(2.6%)	(6.0%)
Property damage	16.0%	2.6%	22.3%
	(5.6%)	(2.9%)	(6.9%)
Controls for offence characteristics	All but Police Area Command, control for offence at category level	Yes	Yes
Controls for hearing characteristics	All but Judicial Officer	Yes	Yes
Controls for prior offending history	Yes	Yes	Yes
Controls for demographic variables	All but SEIFA quartile	Yes	Yes

When the causal impact of AVL is estimated separately for each offence (the “split” model), only two offences, illicit drugs and property damage, are estimated to have an impact greater than 10% and both are estimated to have a positive effect. For these two offences, appearing via AVL is estimated to increase the likelihood of being granted bail by 15% and 18% respectively. The estimates from the generalised random forest indicate that one offence, property damage, has an impact greater than 10%. For this offence, we estimate that appearing via AVL increased the probability of bail by 23%.

These estimates of the causal impact of AVL are much larger than those reported in previous sections, but are also less precise due to the smaller number of observations used in these calculations. As a result, the largest causal impacts from split regressions or generalised random forest models are likely to overestimate the size of the treatment effect.

In contrast, using a multi-level model, we see no offences where the causal impact of AVL is estimated to be greater than 10%. The largest impact is for those who have common assault as their most serious charge, who are estimated to be 5.3% less likely to be granted bail if they appear via AVL. From the generalised random forest estimates, one offence has an impact greater than 10%, property damage. For this offence, we estimate that appearing via AVL increased the probability of bail by 23%.

Thus, out of the 16 offences considered here, only two offences (illicit drugs and property damage) have meaningful differences in the estimated causal impact of AVL. However both of these estimates are positive, suggesting an advantage of appearing via AVL compared with appearing in person at court. The estimates indicate a meaningful difference only in the case of property damage. However, this offence category has the smallest number of bail hearings of all the categories analysed (450 hearings), and our estimates are sensitive to small sample sizes.

DISCUSSION

The aim of this study is to estimate the causal impact of appearing via audio-visual link on the likelihood of being granted bail. We have utilised more than two years of data on first bail hearings in NSW and implemented a simple research design to estimate the causal impact of AVL, comparing those who appeared via AVL to those who appeared in person controlling for possible confounding variables. Due to the large number of possible confounding variables, we have estimated the causal impact of AVL using three different statistical methods to ensure that our conclusions are robust to the estimation approach.

In aggregate, our analysis finds no meaningful differences in the probability of being granted bail for defendants appearing via AVL compared with those appearing in person before the court. We also find no evidence for a causal impact of AVL on bail outcomes for specific subgroups. Estimates by gender, Aboriginality, SEIFA quartile, remoteness of area and offence type are all largely consistent with the estimates of the average impact across all bail hearings. Where there are differences, the vast majority of our estimates suggest that those appearing via AVL are more likely to be granted bail (not less) compared to those who appear in person.

While we find no evidence that the use of AVL for first bail appearances disadvantages defendants in terms of bail decisions, this does not suggest that appearances via AVL are in other ways equivalent to appearing in person. This study should not be taken as an endorsement of the use of AVL for court appearances, or used in lieu of a more holistic evaluation of the use of AVL. Any evaluation of AVL would need to weigh up the relevant costs (the experience of the defendant, procedural justice, concerns about privacy) with the relevant benefits (reduction in costs for both the State and the defendant), along with the possible impact of AVL on outcomes such as the likelihood of bail.

Due to data limitations, we have not been able to assess the impact of AVL on those with intellectual or cognitive disabilities – a group that may face specific challenges appearing via AVL. More fundamentally, our ability to estimate an unbiased causal effect hinges on how unbiased the allocation of AVL is to defendants. Evaluations that utilise explicit random assignment may provide a more credible estimate than the current paper, which exploits the 'as good as random' nature of the current practice.

As AVL becomes more widely used over time, particularly with the changes that have occurred in response to the COVID-19 pandemic, policy makers should not simply assume that the findings of this study will continue to apply. The causal impact of AVL technology may be more dependent on avoiding technical issues, ensuring that defendants feel comfortable and that their privacy is respected and the ability for the court to integrate the technology than any impact of simply appearing on a screen rather than physically being present.

Given the importance of these contextual factors, ongoing monitoring will be required to ensure that appearing via AVL continues to present no disadvantage to defendants in bail determinations. Further, as the use of AVL is expanded, and becomes the default for many types of court hearings, the question most relevant to policy may be how to best to use AVL, rather than whether AVL should be used at all in lieu of in-person appearances.

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APPENDIX

Appendix A: Balance for all variables

Table A1a. Offence characteristics, by appearance type

	Appear in person	Appear via AVL	*p*-value
Granted bail			< 0.01
TRUE	8003 (45%)	3857 (48%)	
FALSE	9900 (55%)	4166 (52%)	
'Show cause' offence			0.09
TRUE	330 (2%)	124 (2%)	
FALSE	17573 (98%)	7899 (98%)	
Median Sentence Ranking (most severe offence)			< 0.01
Mean (SD)	57.6 (23.7)	58.9 (25.1)	
Range	1.0 - 134.0	3.0 - 131.0	
Indictable offence			0.76
TRUE	13483 (75%)	6028 (75%)	
FALSE	4420 (25%)	1995 (25%)	
Hearing was on a weekend			< 0.01
TRUE	2384 (13%)	3761 (47%)	
FALSE	15519 (87%)	4262 (53%)	

Table A1b. Prior offending history, by appearance type

	Appear in person	Appear via AVL	*p*-value
Number of proven prior violent offences in the last two years			0.02
	0.7 (1.3)	0.7 (1.2)	
	0.0 - 17.0	0.0 - 16.0	
Number of proven prior property offences in the last two years			< 0.01
	1.3 (2.9)	1.6 (3.4)	
	0.0 - 51.0	0.0 - 58.0	
Number of proven prior drug offences in the last two years			< 0.01
	0.4 (1.1)	0.6 (1.4)	
	0.0 - 15.0	0.0 - 27.0	
Number of proven prior traffic offences in the last two years			< 0.01
	0.8 (1.8)	0.5 (1.4)	
	0.0 - 29.0	0.0 - 19.0	
Number of proven prior breach offences in the last two years			0.15
	1.7 (3.4)	1.6 (3.6)	
	0.0 - 57.0	0.0 - 60.0	
Number of other proven prior offences in the last two years			< 0.01
	0.6 (1.3)	0.7 (1.5)	
	0.0 - 27.0	0.0 - 31.0	
Number of prior prison sentences			0.23
	0.4 (0.8)	0.5 (0.9)	
	0.0 - 7.0	0.0 - 8.0	

Table A1c. Demographics, by appearance type

	Appear in person	Appear via AVL	*p*-value
Gender			< 0.01
Female	2505 (14%)	1246 (16%)	
Male	15398 (86%)	6777 (84%)	
Age group			< 0.01
18-24	3091 (17%)	1264 (16%)	
25-34	6097 (34%)	2581 (32%)	
35-44	4953 (28%)	2378 (30%)	
45-54	2548 (14%)	1366 (17%)	
55-64	536 (3%)	291 (4%)	
65+	125 (1%)	49 (1%)	
Not recorded	553 (3%)	94 (1%)	
Aboriginality			< 0.01
Aboriginal	7341 (41%)	2598 (32%)	
Non-Aboriginal	10515 (59%)	5381 (67%)	
Unknown	47 (0%)	44 (1%)	
SEIFA			< 0.01
1 (most disadvantaged)	4918 (28%)	1648 (21%)	
2	7965 (45%)	2219 (28%)	
3	3998 (23%)	3029 (38%)	
4 (least disadvantaged)	768 (4%)	1029 (13%)	
Not recorded	254	98	
Remoteness area			< 0.01
Not recorded	253	98	
Inner regional	5033 (29%)	375 (5%)	
Major cities	10729 (61%)	7429 (94%)	
Remote	1888 (11%)	121 (2%)	

Appendix B: Aggregate impact

Table B1. Full regression table for aggregate impact analysis

	Logistic model (marginal effects)	Multi-level model
(Intercept)		62.0% ***
		(3.6%)
avl	2.7% ***	-1.5%
	(0.7%)	(1.1%)
remoteness_areaMajor cities	1.7% *	1.8% +
	(0.8%)	(1.1%)
remoteness_areaRemote	2.7% *	-1.3%
	(1.3%)	(1.5%)
age_cat18-24	-4.6% ***	-4.8% ***
	(0.9%)	(0.9%)
age_cat25-34	-4.7% ***	-4.7% ***
	(0.9%)	(0.9%)
age_cat35-44	-1.3%	-2.0% +
	(1.1%)	(1.0%)
age_cat45-54	-0.0%	-0.9%
	(1.9%)	(1.8%)
age_cat55-64	6.2% +	5.9%
	(3.7%)	(3.6%)
age_cat65+	1.4% +	-0.3%
	(0.8%)	(0.8%)
seifa_qrt2	3.9% ***	1.6% +
	(0.8%)	(0.9%)
seifa_qrt3	7.4% ***	4.2% **
	(1.3%)	(1.4%)
seifa_qrt4	0.1% ***	0.1% **
	(0.0%)	(0.0%)
most_severe	-3.3% ***	-3.9% ***
	(0.3%)	(0.3%)
total	-3.7% ***	-2.8% *
	(0.7%)	(1.1%)
weekend	-13.2% ***	-10.4% ***
	(0.9%)	(1.0%)
indict	-12.0% ***	-8.2% **
	(2.3%)	(2.7%)
show_cause	-9.9% ***	-9.5% ***
	(0.8%)	(0.8%)
genderMale	1.7% *	3.0% ***
	(0.7%)	(0.7%)
Non-Aboriginal	8.0%	7.2%
	(5.4%)	(5.6%)
Aboriginality Unknown	-0.5% +	-0.6% *
	(0.3%)	(0.3%)

Table B1. Full regression table for aggregate impact analysis (continued)

	Logistic model (marginal effects)	Multi-level model
viol_proven	-0.1%	-0.1%
	(0.1%)	(0.1%)
property_proven	-0.4%	-0.6% *
	(0.3%)	(0.3%)
drug_proven	-1.0% ***	-0.8% ***
	(0.2%)	(0.2%)
traffic_proven	0.3%	0.3%
	(0.3%)	(0.2%)
other_proven	-0.5% ***	-0.4% ***
	(0.1%)	(0.1%)
breach_proven	-10.6% ***	-9.1% ***
	(0.5%)	(0.4%)
prison	9.1% ***	62.0% ***
	(2.3%)	(3.6%)
anzsoc_102	-19.7%	-1.5%
	(17.9%)	(1.1%)
anzsoc_103	-22.3%	1.8% +
	(18.0%)	(1.1%)
anzsoc_104	-34.0% +	-1.3%
	(18.1%)	(1.5%)
anzsoc_105	-17.6%	-4.8% ***
	(18.2%)	(0.9%)
anzsoc_106	-25.0%	-4.7% ***
	(18.2%)	(0.9%)
anzsoc_107	-31.5% +	-2.0% +
	(18.0%)	(1.0%)
anzsoc_108	-23.6%	-0.9%
	(17.9%)	(1.8%)
anzsoc_109	-24.8%	5.9%
	(18.0%)	(3.6%)
anzsoc_110	-23.9%	-0.3%
	(18.0%)	(0.8%)
anzsoc_111	-23.7%	1.6% +
	(18.1%)	(0.9%)
anzsoc_112	-12.4%	4.2% **
	(18.1%)	(1.4%)
anzsoc_113	-22.7%	0.1% **
	(18.0%)	(0.0%)
anzsoc_114	-34.7% +	-3.9% ***
	(18.0%)	(0.3%)
anzsoc_115	-10.1%	-2.8% *
	(17.9%)	(1.1%)
anzsoc_116	-32.4% +	-10.4% ***
	(18.5%)	(1.0%)
N	25,573	24,338

Notes. + < 0.1, * *p* <. 05, ** *p* <. 01, *** *p* < .001., NaN stands for Not A Number and means that the value could not be estimated

Appendix C: Gender

Table C1. Full regression table for analysis by gender

	Female Logistic model (marginal effects)	Male Logistic model (marginal effects)	Multi-level model
(Intercept)			62.1% ***
			(3.6%)
avl	3.6% +	2.6% **	
	(1.9%)	(0.8%)	
avl:genderFemale			-1.9%
			(1.9%)
avl:genderMale			-1.4%
			(1.2%)
remoteness_areaMajor cities	1.6%	1.6% +	1.8% +
	(2.0%)	(0.9%)	(1.1%)
remoteness_areaRemote	6.7% *	2.0%	-1.3%
	(3.2%)	(1.4%)	(1.5%)
age_cat25-34	-4.1% +	-4.7% ***	-4.8% ***
	(2.2%)	(1.0%)	(0.9%)
age_cat35-44	-2.6%	-5.0% ***	-4.7% ***
	(2.3%)	(1.0%)	(0.9%)
age_cat45-54	0.7%	-1.7%	-2.0% +
	(2.8%)	(1.1%)	(1.0%)
age_cat55-64	1.4%	-0.3%	-0.9%
	(5.7%)	(2.0%)	(1.8%)
age_cat65+	18.6%	5.0%	5.9%
	(11.6%)	(3.9%)	(3.6%)
seifa_qrt2	3.5% +	1.0%	-0.3%
	(2.1%)	(0.8%)	(0.8%)
seifa_qrt3	2.3%	4.2% ***	1.6% +
	(2.3%)	(0.9%)	(0.9%)
seifa_qrt4	8.8% **	7.0% ***	4.2% **
	(3.4%)	(1.4%)	(1.4%)
most_severe	0.1%	0.1% ***	0.1% **
	(0.0%)	(0.0%)	(0.0%)
total	-3.9% ***	-3.3% ***	-3.9% ***
	(0.8%)	(0.3%)	(0.3%)
weekend	-3.8% +	-3.8% ***	-2.8% *
	(2.0%)	(0.8%)	(1.1%)
indict	-13.1% ***	-12.7% ***	-10.4% ***
	(2.3%)	(1.0%)	(1.0%)
show_cause	-9.3%	-13.3% ***	-8.2% **
	(5.9%)	(2.8%)	(2.7%)
genderMale			-9.6% ***
			(1.0%)
Non-Aboriginal	-0.0%	1.9% **	3.0% ***
	(1.7%)	(0.7%)	(0.7%)
Aboriginality Unknown	13.1%	7.0%	7.2%
	(13.8%)	(5.9%)	(5.6%)
viol_proven	-0.9%	-0.5%	-0.6% *
	(0.7%)	(0.3%)	(0.3%)
property_proven	-0.5% +	0.1%	-0.1%
	(0.3%)	(0.1%)	(0.1%)

Table C1. Full regression table for analysis by gender (continued)

	Female Logistic model (marginal effects)	Male Logistic model (marginal effects)	Multi-level model
drug_proven	-1.1%	-0.4%	-0.6% *
	(0.7%)	(0.3%)	(0.3%)
traffic_proven	-0.9% +	-1.0% ***	-0.8% ***
	(0.5%)	(0.2%)	(0.2%)
other_proven	-0.4%	0.4%	0.3%
	(0.6%)	(0.3%)	(0.2%)
breach_proven	-0.3%	-0.6% ***	-0.4% ***
	(0.2%)	(0.1%)	(0.1%)
prison	-11.4% ***	-10.6% ***	-9.1% ***
	(1.4%)	(0.5%)	(0.4%)
age_catNot recorded	4.6%	10.2% ***	
	(5.3%)	(2.6%)	
anzsoc_103	-27.5%	-22.2%	
	(17.3%)	(18.2%)	
anzsoc_104	-28.2% ***	-33.7% +	
	(7.5%)	(18.2%)	
anzsoc_105	-10.2%	-17.5%	
	(9.8%)	(18.4%)	
anzsoc_106	-5.8%	-26.4%	
	(9.8%)	(18.4%)	
anzsoc_107	-9.8% *	-33.3% +	
	(4.7%)	(18.1%)	
anzsoc_108	-9.0% **	-24.0%	
	(2.9%)	(18.1%)	
anzsoc_109	-10.6% **	-24.9%	
	(3.8%)	(18.1%)	
anzsoc_110	-10.5% **	-24.4%	
	(3.9%)	(18.1%)	
anzsoc_111	-10.2%	-24.7%	
	(8.4%)	(18.2%)	
anzsoc_112	3.1%	-13.4%	
	(5.3%)	(18.2%)	
anzsoc_113	-6.1%	-23.7%	
	(4.2%)	(18.1%)	
anzsoc_114	-20.2% ***	-35.5% +	
	(5.1%)	(18.2%)	
anzsoc_115	8.1% ***	-11.3%	
	(2.4%)	(18.1%)	
anzsoc_116	-18.8% +	-32.7% +	
	(11.0%)	(18.8%)	
anzsoc_102		-21.2%	
		(18.1%)	
N	3,690	21,883	24,338

Notes. + < 0.1, * *p* <. 05, ** *p* <. 01, *** *p* < .001., NaN stands for Not A Number and means that the value could not be estimated
Not enough women with ANZSOC category 02 to include this indicator in the regression

Appendix D: Aboriginal status

Table D1. Full regression table for analysis by Aboriginal status

	Aboriginal Logistic model (marginal effects)	Non-Aboriginal Logistic model (marginal effects)	Multi-level model
(Intercept)			62.0% ***
			(3.6%)
avl	2.9% *	2.5% **	
	(1.2%)	(0.9%)	
avl:Aboriginal			-1.8%
			(1.5%)
avl:Non-Aboriginal			-1.4%
			(1.2%)
avl:Aboriginality Unknown			1.6%
			(11.0%)
remoteness_areaMajor cities	-0.1%	3.1% **	1.8% +
	(1.2%)	(1.1%)	(1.1%)
remoteness_areaRemote	2.7% +	0.8%	-1.3%
	(1.5%)	(2.4%)	(1.5%)
age_cat25-34	-3.3% *	-5.9% ***	-4.8% ***
	(1.3%)	(1.2%)	(0.9%)
age_cat35-44	-3.2% *	-6.0% ***	-4.6% ***
	(1.4%)	(1.2%)	(0.9%)
age_cat45-54	-0.2%	-2.4% +	-2.0% +
	(1.7%)	(1.4%)	(1.0%)
age_cat55-64	-0.1%	-0.8%	-0.9%
	(3.9%)	(2.2%)	(1.8%)
age_cat65+	7.8%	4.5%	5.9% +
	(9.9%)	(4.1%)	(3.6%)
seifa_qrt2	1.9%	1.3%	-0.3%
	(1.2%)	(1.0%)	(0.8%)
seifa_qrt3	3.4% *	4.3% ***	1.6% +
	(1.5%)	(1.0%)	(0.9%)
seifa_qrt4	6.6% +	7.1% ***	4.2% **
	(3.4%)	(1.4%)	(1.4%)
most_severe	0.1% ***	0.1% ***	0.1% **
	(0.0%)	(0.0%)	(0.0%)
total	-3.6% ***	-3.2% ***	-3.9% ***
	(0.5%)	(0.4%)	(0.3%)
weekend	-3.8% **	-3.6% ***	-2.8% *
	(1.2%)	(1.0%)	(1.1%)
indict	-13.4% ***	-12.2% ***	-10.4% ***
	(1.4%)	(1.2%)	(1.0%)
show_cause	-19.6% ***	-10.3% ***	-8.2% **
	(4.7%)	(3.0%)	(2.7%)
genderMale	-10.4% ***	-9.0% ***	-9.5% ***
	(1.3%)	(1.2%)	(0.8%)
Non-Aboriginal			2.8% ***
			(0.8%)
Aboriginality Unknown			5.5%
			(7.9%)

Table D1. Full regression table for analysis by Aboriginal status (continued)

	Aboriginal Logistic model (marginal effects)	Non-Aboriginal Logistic model (marginal effects)	Multi-level model
viol_proven	-0.6%	-0.4%	-0.6% *
	(0.4%)	(0.4%)	(0.3%)
property_proven	0.0%	-0.1%	-0.1%
	(0.2%)	(0.2%)	(0.1%)
drug_proven	-0.4%	-0.3%	-0.6% *
	(0.5%)	(0.4%)	(0.3%)
traffic_proven	-0.8% **	-1.1% ***	-0.8% ***
	(0.3%)	(0.3%)	(0.2%)
other_proven	0.4%	0.2%	0.3%
	(0.4%)	(0.3%)	(0.2%)
breach_proven	-0.3% *	-0.7% ***	-0.4% ***
	(0.1%)	(0.2%)	(0.1%)
prison	-8.7% ***	-12.8% ***	-9.1% ***
	(0.7%)	(0.7%)	(0.4%)
age_catNot recorded	15.9% ***	5.7% *	
	(3.9%)	(2.9%)	
anzsoc_102	39.6% ***	-34.5% *	
	(1.0%)	(14.9%)	
anzsoc_103	35.0% ***	-37.2% *	
	(4.6%)	(15.1%)	
anzsoc_104	29.3% ***	-51.3% ***	
	(3.8%)	(15.2%)	
anzsoc_105	49.0% ***	-36.6% *	
	(5.3%)	(15.4%)	
anzsoc_106	37.7% ***	-42.6% **	
	(5.5%)	(15.6%)	
anzsoc_107	29.7% ***	-47.4% **	
	(2.0%)	(15.0%)	
anzsoc_108	39.7% ***	-41.4% **	
	(1.4%)	(14.9%)	
anzsoc_109	36.2% ***	-40.7% **	
	(2.5%)	(15.0%)	
anzsoc_110	39.1% ***	-40.3% **	
	(2.5%)	(15.0%)	
anzsoc_111	42.6% ***	-42.6% **	
	(3.6%)	(15.1%)	
anzsoc_112	53.9% ***	-31.5% *	
	(3.4%)	(15.2%)	
anzsoc_113	38.8% ***	-39.0% **	
	(2.0%)	(15.0%)	
anzsoc_114	23.4% ***	-48.6% **	
	(2.6%)	(15.0%)	
anzsoc_115	49.4% ***	-24.7% +	
	(0.9%)	(14.9%)	
anzsoc_116	30.4% **	-46.3% **	
	(10.0%)	(15.9%)	
N	9,896	15,601	24,338

Note. + < 0.1, * *p* <. 05, ** *p* <. 01, *** *p* < .001., NaN stands for Not A Number and means that the value could not be estimated

Appendix E: SEIFA quartile

Table E1. Full regression table for analysis by SEIFA quartile

	Multi-level model	Quartile 1 Logistic model (marginal effects)	Quartile 2 Logistic model (marginal effects)	Quartile 3 Logistic model (marginal effects)	Quartile 4 Logistic model (marginal effects)
(Intercept)	62.7% ***				
	(3.6%)				
avl		-2.0%	5.3% ***	3.3% *	1.1%
		(5625185.1%)	(1.2%)	(1.3%)	(NaN)
avl:seifa_qrt1	-4.5% **				
	(1.6%)				
avl:seifa_qrt2	1.3%				
	(1.5%)				
avl:seifa_qrt3	-1.3%				
	(1.5%)				
avl:seifa_qrt4	-3.7%				
	(2.5%)				
remoteness_areaMajor cities	1.8% +	9.1%	-0.3%	-1.3%	-8.1%
	(1.1%)	(5545395.3%)	(1.1%)	(1.8%)	(NaN)
remoteness_areaRemote	-1.7%	8.7%	-1.5%	-17.1% *	5.2%
	(1.5%)	(17485797.2%)	(2.0%)	(8.5%)	(NaN)
age_cat25-34	-4.8% ***	-2.4%	-5.1% ***	-6.2% ***	-1.0%
	(0.9%)	(11134383.1%)	(1.4%)	(1.8%)	(NaN)
age_cat35-44	-4.7% ***	-2.9%	-5.7% ***	-5.8% **	1.7%
	(0.9%)	(3347720.4%)	(1.4%)	(1.8%)	(NaN)
age_cat45-54	-2.0% +	-3.1%	-0.5%	-1.3%	-0.3%
	(1.0%)	(11186804.9%)	(1.7%)	(2.0%)	(NaN)
age_cat55-64	-0.9%	-1.6%	-2.0%	5.5%	-1.3%
	(1.8%)	(13398387.6%)	(3.2%)	(3.4%)	(NaN)
age_cat65+	5.8%	12.0%	2.5%	3.5%	11.4%
	(3.6%)	(31132771.8%)	(6.4%)	(6.0%)	(NaN)
Non-Aboriginal	3.0% ***	0.8%	0.9%	3.0% *	3.6%
	(0.7%)	(184758.7%)	(1.0%)	(1.3%)	(NaN)
Aboriginality Unknown	7.6%	-3.7%	-2.1%	19.1% *	27.1%
	(5.6%)	(4733860.8%)	(10.7%)	(8.9%)	(NaN)
most_severe	0.1% **	0.1%	0.0%	0.2% ***	0.2%
	(0.0%)	(NaN)	(0.0%)	(0.0%)	(NaN)
total	-3.9% ***	-4.0%	-3.5% ***	-2.5% ***	-2.7%
	(0.3%)	(4447596.7%)	(0.5%)	(0.6%)	(NaN)
weekend	-2.8% *	-2.3%	-3.4% **	-4.3% **	-4.3%
	(1.1%)	(4368290.1%)	(1.2%)	(1.4%)	(NaN)
indict	-10.4% ***	-13.4%	-11.9% ***	-12.7% ***	-13.7%
	(1.0%)	(62197023.2%)	(1.4%)	(1.7%)	(NaN)
show_cause	-8.2% **	-7.9%	-19.2% ***	-9.4% *	-8.6%
	(2.7%)	(26796817.1%)	(4.3%)	(4.7%)	(NaN)
genderMale	-9.4% ***	-9.8%	-11.3% ***	-7.8% ***	-10.0%
	(0.8%)	(35676979.0%)	(1.3%)	(1.6%)	(NaN)
seifa_qrt2	-1.7% +				
	(0.9%)				
seifa_qrt3	0.8%				
	(1.1%)				
seifa_qrt4	4.8% *				
	(2.0%)				

Table E1. Full regression table for analysis by SEIFA quartile (continued)

	Multi-level model	Quartile 1 Logistic model (marginal effects)	Quartile 2 Logistic model (marginal effects)	Quartile 3 Logistic model (marginal effects)	Quartile 4 Logistic model (marginal effects)
viol_proven	-0.6% *	-0.4%	-0.6%	-1.0% +	0.9%
	(0.3%)	(198900.3%)	(0.4%)	(0.5%)	(NaN)
property_proven	-0.1%	-0.2%	0.2%	-0.4% +	0.0%
	(0.1%)	(81447.9%)	(0.2%)	(0.2%)	(NaN)
drug_proven	-0.6% *	-1.1%	-1.3% *	0.3%	-0.9%
	(0.3%)	(1079040.1%)	(0.5%)	(0.4%)	(NaN)
traffic_proven	-0.8% ***	-0.3%	-0.8% **	-1.6% ***	-3.0%
	(0.2%)	(NaN)	(0.3%)	(0.4%)	(NaN)
other_proven	0.3%	-0.1%	0.1%	0.5%	0.4%
	(0.2%)	(768176.6%)	(0.4%)	(0.5%)	(NaN)
breach_proven	-0.4% ***	-0.5%	-0.3% +	-0.7% ***	-0.7%
	(0.1%)	(2232364.6%)	(0.2%)	(0.2%)	(NaN)
prison	-9.1% ***	-11.9%	-11.8% ***	-7.7% ***	-14.1%
	(0.4%)	(26847401.4%)	(0.8%)	(0.9%)	(NaN)
age_catNot recorded		13.0%	10.6% **	3.3%	7.4%
		(71394824.9%)	(3.5%)	(4.6%)	(NaN)
anzsoc_102		-58.1%	-10.9%	-27.5%	57.4%
		(250538090003.7%)	(50.6%)	(24.1%)	(NaN)
anzsoc_103		-66.0%	-12.0%	-22.6%	37.6%
		(250538090022.5%)	(50.6%)	(24.4%)	(NaN)
anzsoc_104		-67.0%	-24.1%	-45.8% +	35.5%
		(250538072313.0%)	(50.7%)	(24.7%)	(NaN)
anzsoc_105		-49.2%	-8.4%	-26.0%	38.2%
		(250538070299.3%)	(50.8%)	(24.9%)	(NaN)
anzsoc_106		-67.6%	-12.1%	-25.0%	-0.0%
		(250538072442.2%)	(50.9%)	(24.8%)	(NaN)
anzsoc_107		-69.1%	-25.0%	-36.5%	48.4%
		(250538107160.8%)	(50.6%)	(24.2%)	(NaN)
anzsoc_108		-61.5%	-16.2%	-29.9%	55.5%
		(250538108841.6%)	(50.6%)	(24.2%)	(NaN)
anzsoc_109		-59.6%	-16.5%	-33.4%	52.8%
		(250538109136.9%)	(50.6%)	(24.2%)	(NaN)
anzsoc_110		-62.6%	-13.0%	-30.6%	46.5%
		(250538071354.7%)	(50.6%)	(24.2%)	(NaN)
anzsoc_111		-56.5%	-14.2%	-32.6%	42.1%
		(250538089995.0%)	(50.7%)	(24.5%)	(NaN)
anzsoc_112		-53.5%	3.1%	-23.2%	55.8%
		(250538050717.5%)	(50.7%)	(24.4%)	(NaN)
anzsoc_113		-59.3%	-12.9%	-32.5%	51.0%
		(250502356212.9%)	(50.6%)	(24.2%)	(NaN)
anzsoc_114		-73.0%	-20.7%	-47.1% +	37.9%
		(250538097975.2%)	(50.6%)	(24.3%)	(NaN)
anzsoc_115		-49.0%	-0.4%	-17.1%	63.4%
		(250538090013.7%)	(50.6%)	(24.1%)	(NaN)
anzsoc_116		-82.5%	-5.4%	-39.3%	28.4%
		(250538090004.9%)	(51.8%)	(25.2%)	(NaN)
N	24,338	6,565	10,184	7,027	1,797

Note. + < 0.1, * *p* <. 05, ** *p* <. 01, *** *p* < .001., NaN stands for Not A Number and means that the value could not be estimated

Appendix F: Remoteness area

Table F1. Full regression table for analysis by remoteness area

	Multi-level model	Inner regional Logistic model (marginal effects)	Major cities Logistic model (marginal effects)	Remoteness Logistic model (marginal effects)
(Intercept)	63.0% ***			
	(3.1%)			
avl		2.1%	3.1% ***	3.8%
		(1333138.8%)	(0.8%)	(NaN)
avl:remoteness_areaInner regional	-2.0%			
	(2.8%)			
avl:remoteness_areaMajor cities	-1.7%			
	(1.2%)			
avl:remoteness_areaRemote	4.5%			
	(4.6%)			
remoteness_areaMajor cities	2.1% +			
	(1.2%)			
remoteness_areaRemote	-1.7%			
	(1.5%)			
age_cat25-34	-5.0% ***	-4.4%	-5.5% ***	3.1%
	(0.9%)	(1871659.5%)	(1.1%)	(NaN)
age_cat35-44	-4.6% ***	-5.8%	-5.2% ***	3.2%
	(0.9%)	(1166033.0%)	(1.1%)	(NaN)
age_cat45-54	-2.0% +	-2.1%	-1.7%	2.1%
	(1.0%)	(2235620.2%)	(1.3%)	(NaN)
age_cat55-64	-0.6%	-5.6%	1.2%	-2.8%
	(1.8%)	(6318046.8%)	(2.2%)	(NaN)
age_cat65+	5.0%	8.8%	5.5%	4.7%
	(3.6%)	(17847061.1%)	(4.3%)	(NaN)
Non-Aboriginal	2.9% ***	-0.4%	2.6% ***	0.9%
	(0.7%)	(335503.1%)	(0.8%)	(NaN)
Aboriginality Unknown	8.2%	6.2%	11.7% *	-42.7%
	(5.6%)	(10727009.2%)	(6.0%)	(NaN)
most_severe	0.1% ***	0.1%	0.1% ***	0.1%
	(0.0%)	(251167.6%)	(0.0%)	(NaN)
total	-3.7% ***	-3.3%	-3.0% ***	-5.4%
	(0.3%)	(2714940.1%)	(0.4%)	(NaN)
weekend	-3.1% **	-2.5%	-4.5% ***	-1.6%
	(1.1%)	(349203.1%)	(0.9%)	(NaN)
indict	-12.2% ***	-9.0%	-13.4% ***	-17.6%
	(0.9%)	(5334347.8%)	(1.1%)	(NaN)
show_cause	-12.0% ***	-9.8%	-12.0% ***	-23.2%
	(2.6%)	(17852477.4%)	(2.9%)	(NaN)
genderMale	-9.8% ***	-9.9%	-9.5% ***	-11.7%
	(0.8%)	(14308426.0%)	(1.0%)	(NaN)
seifa_qrt2	-0.3%	7.5%	0.3%	-2.6%
	(0.8%)	(16115537.2%)	(1.0%)	(NaN)
seifa_qrt3	1.9% *	10.8%	2.8% **	-15.6%
	(0.9%)	(12555038.0%)	(1.0%)	(NaN)
seifa_qrt4	4.4% **	23.7%	6.1% ***	24.9%
	(1.4%)	(25241397.6%)	(1.4%)	(NaN)
viol_proven	-0.6% *	0.0%	-0.6% +	-0.7%
	(0.3%)	(4101.1%)	(0.3%)	(NaN)

Table F1. Full regression table for analysis by remoteness area (continued)

	Multi-level model	Inner regional Logistic model (marginal effects)	Major cities Logistic model (marginal effects)	Remoteness Logistic model (marginal effects)
property_proven	-0.1%	-0.2%	-0.1%	1.0%
	(0.1%)	(109510.5%)	(0.1%)	(NaN)
drug_proven	-0.5% +	-1.1%	-0.3%	-2.2%
	(0.3%)	(1135511.4%)	(0.3%)	(NaN)
traffic_proven	-0.8% ***	-0.8%	-1.0% ***	-1.3%
	(0.2%)	(678757.7%)	(0.2%)	(NaN)
other_proven	0.3%	-0.7%	0.6% *	-0.2%
	(0.2%)	(771916.3%)	(0.3%)	(NaN)
breach_proven	-0.5% ***	-0.3%	-0.6% ***	-0.1%
	(0.1%)	(161009.9%)	(0.1%)	(NaN)
prison	-9.3% ***	-10.9%	-10.3% ***	-13.9%
	(0.4%)	(7135142.5%)	(0.6%)	(NaN)
age_catNot recorded		8.5%	7.0% *	30.6%
		(NaN)	(2.7%)	(NaN)
anzsoc_102		40.4%	-20.9%	-57.6%
		(92872302752.5%)	(18.6%)	(NaN)
anzsoc_103		39.6%	-23.2%	-66.7%
		(92879445721.4%)	(18.7%)	(NaN)
anzsoc_104		32.2%	-36.5% +	-77.7%
		(92879452151.3%)	(18.8%)	(NaN)
anzsoc_105		33.2%	-14.2%	-82.3%
		(92879434117.0%)	(19.0%)	(NaN)
anzsoc_106		46.7%	-27.7%	-81.9%
		(92879445491.3%)	(19.0%)	(NaN)
anzsoc_107		30.1%	-34.0% +	-62.9%
		(92879457886.7%)	(18.6%)	(NaN)
anzsoc_108		36.6%	-25.7%	-54.6%
		(92872296688.2%)	(18.6%)	(NaN)
anzsoc_109		33.6%	-25.9%	-58.3%
		(92879458215.4%)	(18.6%)	(NaN)
anzsoc_110		40.1%	-25.9%	-64.0%
		(92879445695.7%)	(18.6%)	(NaN)
anzsoc_111		34.5%	-23.4%	-69.9%
		(92879452156.3%)	(18.8%)	(NaN)
anzsoc_112		46.8%	-13.4%	-46.1%
		(92879445494.5%)	(18.8%)	(NaN)
anzsoc_113		38.5%	-24.2%	-58.4%
		(92872309231.7%)	(18.6%)	(NaN)
anzsoc_114		25.6%	-34.7% +	-82.5%
		(92879452150.9%)	(18.7%)	(NaN)
anzsoc_115		51.8%	-11.3%	-51.6%
		(92872302568.3%)	(18.6%)	(NaN)
anzsoc_116		44.0%	-37.0% +	-76.6%
		(92872309234.0%)	(19.2%)	(NaN)
N	24,338	5,407	18,157	2,009

Note. + < 0.1, * *p* <. 05, ** *p* <. 01, *** *p* < .001., NaN stands for Not A Number and means that the value could not be estimated.

Appendix G: Most serious offence

Table G1. Full regression table for analysis by most serious offence

	Serious assault resulting in injury	Common assault	Stalking	Unlawful entry with intent/burglary, break and enter	Illegal use of a motor vehicle	Theft (except motor vehicles)	Receive or handle proceeds of crime	Obtain benefit by deception
(Intercept)								
avl	0.4%	-4.9%	-1.5%	-2.8%	0.9%	2.5%	12.4% ***	-2.7%
	(2.3%)	(NaN)	(2.6%)	(3.2%)	(NaN)	(NaN)	(3.4%)	(3.4%)
breach_proven	-1.0% +	-2.1%	-0.9% *	-0.4%	-0.5%	0.6%	0.6%	-0.2%
	(0.6%)	(NaN)	(0.4%)	(0.4%)	(NaN)	(NaN)	(0.5%)	(0.5%)
drug_proven	0.3%	-4.5%	-1.4%	-0.7%	-3.1%	-1.3%	-2.0% +	-3.9% *
	(1.0%)	(NaN)	(1.4%)	(1.5%)	(NaN)	(NaN)	(1.0%)	(1.6%)
genderMale	-18.0% ***	-3.0%	-18.9% ***	-15.1% ***	-7.8%	0.5%	-5.6%	-8.4% *
	(3.1%)	(NaN)	(3.6%)	(4.3%)	(NaN)	(NaN)	(3.8%)	(3.7%)
indict	0.0%	305.8%	0.0%	0.0%	0.0%	-320.0%	-10.9% ***	-18.4%
	(0.0%)	(NaN)	(0.0%)	(0.0%)	(NaN)	(NaN)	(3.0%)	(15.2%)
Non-Aboriginal	6.8% **	2.7%	2.2%	1.2%	-2.0%	-4.1%	-4.9%	0.3%
	(2.1%)	(NaN)	(2.2%)	(2.7%)	(NaN)	(NaN)	(3.2%)	(3.4%)
Aboriginality Unknown	35.5%	48.0%	10.9%	-23.7% ***	-22.9%	55.7%	-0.3%	23.8%
	(32.0%)	(NaN)	(27.4%)	(1.9%)	(NaN)	(NaN)	(45.4%)	(20.8%)
most_severe	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	(0.0%)	(NaN)	(0.0%)	(0.0%)	(NaN)	(NaN)	(0.0%)	(0.0%)
other_proven	-0.9%	-0.4%	-0.5%	-0.8%	-1.0%	3.2%	0.4%	0.8%
	(1.2%)	(NaN)	(1.2%)	(1.1%)	(NaN)	(NaN)	(0.9%)	(1.8%)
prison	-10.7% ***	-13.3%	-16.4% ***	-8.6% ***	-6.3%	-13.0%	-9.5% ***	-8.9% ***
	(2.1%)	(NaN)	(2.2%)	(2.2%)	(NaN)	(NaN)	(1.9%)	(2.1%)
property_proven	-0.4%	-1.1%	-0.1%	-0.3%	-0.4%	0.3%	-0.1%	-0.1%
	(0.8%)	(NaN)	(0.7%)	(0.4%)	(NaN)	(NaN)	(0.5%)	(0.5%)

Table G1. Full regression table for analysis by most serious offence (continued)

	Serious assault resulting in injury	Common assault	Stalking	Unlawful entry with intent/burglary, break and enter	Illegal use of a mo-tor vehicle	Theft (except motor vehicles)	Receive or handle proceeds of crime	Obtain benefit by deception
remoteness_ areaMajor cities	1.3%	1.0%	1.3%	0.2%	5.7%	-8.9%	-1.8%	10.1% *
	(2.4%)	(NaN)	(2.6%)	(3.2%)	(NaN)	(NaN)	(4.3%)	(4.1%)
remoteness_ areaRemote	0.3%	6.2%	2.8%	6.1%	17.5%	17.7%	13.3% +	11.5%
	(3.9%)	(NaN)	(3.9%)	(5.1%)	(NaN)	(NaN)	(7.3%)	(7.8%)
seifa_qrt2	2.3%	5.1%	-1.6%	-0.2%	3.8%	-4.3%	1.1%	-0.8%
	(2.3%)	(NaN)	(2.4%)	(3.0%)	(NaN)	(NaN)	(4.0%)	(4.1%)
seifa_qrt3	0.5%	13.4%	4.0%	6.6% +	-2.6%	4.3%	9.8% *	-0.0%
	(2.6%)	(NaN)	(2.8%)	(3.7%)	(NaN)	(NaN)	(4.1%)	(4.4%)
seifa_qrt4	15.0% ***	16.0%	7.4%	12.6% +	11.4%	15.7%	9.8%	6.9%
	(4.3%)	(NaN)	(4.6%)	(6.6%)	(NaN)	(NaN)	(6.7%)	(6.3%)
show_cause	-12.2% ***	0.0%	0.0%	-2.1%	-217.2%	0.0%	0.0%	-3.4%
	(3.5%)	(NaN)	(0.0%)	(25.3%)	(NaN)	(NaN)	(0.0%)	(26.9%)
total	-2.2% *	-3.1%	-4.3% ***	-2.6% **	-4.6%	-3.4%	-2.4% +	-4.6% ***
	(1.0%)	(NaN)	(1.2%)	(0.9%)	(NaN)	(NaN)	(1.4%)	(1.2%)
traffic_proven	-0.1%	0.6%	-1.4%	0.3%	0.6%	-0.2%	-0.8%	-0.4%
	(0.7%)	(NaN)	(0.9%)	(0.8%)	(NaN)	(NaN)	(0.8%)	(0.9%)
viol_proven	-3.3% **	0.2%	0.1%	-0.1%	1.6%	2.9%	1.7%	3.0% +
	(1.0%)	(NaN)	(0.9%)	(1.5%)	(NaN)	(NaN)	(1.7%)	(1.7%)
weekend	1.0%	-3.6%	0.6%	-2.5%	-4.4%	4.0%	-10.9% **	-2.6%
	(2.3%)	(NaN)	(2.6%)	(3.3%)	(NaN)	(NaN)	(3.5%)	(3.6%)
N	2,578	776	2,422	1,189	457	515	1,124	953

Table G1. Full regression table for analysis by most serious offence (continued)

	Deal or traffic in illicit drugs - non-commercial quantity	Possess illicit drugs	Property damage	Criminal intent	Drive while licence disqualified or suspended	Breach of bond - supervised	Serious assault resulting in injury	Breach of violence order	Multi-level model
(Intercept)									61.7%
									(3.7%)
avl	5.9%	9.5%	21.7% ***	-5.0%	-5.7%	3.5%	-0.4%	1.4%	
	(4.2%)	(NaN)	(6.2%)	(NaN)	(102678703.2%)	(2.9%)	(5.1%)	(NaN)	
breach_proven	-0.4%	-0.5%	0.0%	0.1%	0.4%	-0.2%	-0.1%	-0.8%	-0.4%
	(0.8%)	(NaN)	(0.9%)	(NaN)	(1.0%)	(0.3%)	(0.9%)	(NaN)	(0.1%)
drug_proven	-2.0%	1.6%	-1.5%	-0.5%	-2.4%	0.6%	-0.4%	-1.0%	-0.6%
	(1.5%)	(NaN)	(3.0%)	(NaN)	(11160728.6%)	(1.0%)	(1.8%)	(NaN)	(0.3%)
genderMale	-10.0% *	-0.4%	-2.9%	-11.5%	-7.6%	-9.7% ***	-0.1%	-14.3%	-9.5%
	(5.0%)	(NaN)	(6.2%)	(NaN)	(22321457.2%)	(2.8%)	(6.1%)	(NaN)	(0.8%)
indict	0.0%	-314.8%	0.0%	-9.2%	28.1%	-11.4% ***	-8.0%	-4.0%	-10.4%
	(0.0%)	(NaN)	(0.0%)	(NaN)	(107142994.6%)	(2.9%)	(5.2%)	(NaN)	(1.0%)
Non-Aboriginal	3.5%	-5.5%	-9.5% +	0.2%	4.7%	4.6% +	-1.5%	4.1%	3.0%
	(4.4%)	(NaN)	(5.0%)	(NaN)	(NaN)	(2.4%)	(4.3%)	(NaN)	(0.7%)
Aboriginality Unknown	10.8%			70.4%	62.7%	-54.7% ***		40.3%	7.2%
	(19.4%)			(NaN)	(162107350897.3%)	(1.8%)		(NaN)	(5.5%)
most_severe	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
	(0.0%)	(NaN)	(0.0%)	(NaN)	(0.0%)	(0.0%)	(0.0%)	(NaN)	(0.0%)
other_proven	-1.3%	0.5%	0.9%	-0.3%	-4.5%	-0.0%	0.2%	0.5%	0.3%
	(2.2%)	(NaN)	(1.8%)	(NaN)	(11160728.6%)	(1.0%)	(1.9%)	(NaN)	(0.2%)
prison	-12.4% **	-6.6%	-6.9% +	-12.1%	-18.8%	-6.6% ***	-15.2% ***	-11.7%	-9.1%
	(4.7%)	(NaN)	(3.7%)	(NaN)	(62500080.2%)	(1.6%)	(3.5%)	(NaN)	(0.4%)

Table G1. Full regression table for analysis by most serious offence (continued)

	Deal or traffic in illicit drugs - non-commercial quantity	Possess illicit drugs	Property damage	Criminal intent	Drive while licence disqualified or suspended	Breach of bond - supervised	Serious assault resulting in injury	Breach of violence order	Multi-level model
property_proven	-0.6%	0.6%	-1.5% *	-0.7%	-1.8%	0.7%	2.1% +	0.2%	-0.1%
	(1.0%)	(NaN)	(0.7%)	(NaN)	(5580364.3%)	(0.5%)	(1.3%)	(NaN)	(0.1%)
remoteness_ areaMajor cities	-5.1%	1.4%	4.1%	1.9%	12.9%	2.6%	7.2%	0.6%	1.7%
	(5.5%)	(NaN)	(6.0%)	(NaN)	(62500080.2%)	(3.0%)	(5.8%)	(NaN)	(1.0%)
remoteness_ areaRemote	1.7%	-4.1%	11.1%	-4.9%	-1.7%	3.4%	8.1%	3.2%	-1.3%
	(10.2%)	(NaN)	(10.3%)	(NaN)	(13392874.3%)	(4.5%)	(9.2%)	(NaN)	(1.4%)
seifa_qrt2	5.5%	0.1%	13.5% *	1.9%	-2.5%	2.7%	0.3%	1.2%	-0.3%
	(4.6%)	(NaN)	(6.3%)	(NaN)	(4464291.4%)	(2.9%)	(6.0%)	(NaN)	(0.8%)
seifa_qrt3	4.8%	9.3%	10.6%	-1.4%	-5.6%	4.0%	0.8%	3.8%	1.6%
	(4.6%)	(NaN)	(7.0%)	(NaN)	(11160728.6%)	(3.2%)	(6.2%)	(NaN)	(1.0%)
seifa_qrt4	0.3%	8.9%	9.2%	-0.7%	-12.4%	6.6%	5.7%	7.0%	4.2%
	(6.1%)	(NaN)	(15.7%)	(NaN)	(35714331.5%)	(5.0%)	(9.2%)	(NaN)	(1.4%)
show_cause	-300.3% ***	0.0%	0.0%	-6.5%	0.0%	-32.2%	-286.8% ***	292.4%	-8.3%
	(21.6%)	(NaN)	(0.0%)	(NaN)	(0.0%)	(32.6%)	(50.7%)	(NaN)	(2.7%)
total	-2.5% +	4.8%	-11.7% **	-2.9%	-6.8%	-7.2% ***	-6.6% **	-10.7%	-4.0%
	(1.3%)	(NaN)	(4.4%)	(NaN)	(NaN)	(1.2%)	(2.2%)	(NaN)	(0.3%)

Table G1. Full regression table for analysis by most serious offence (continued)

	Deal or traffic in illicit drugs - non-commercial quantity	Possess illicit drugs	Property damage	Criminal intent	Drive while licence disqualified or suspended	Breach of bond - supervised	Serious assault resulting in injury	Breach of violence order	Multi-level model
traffic_proven	-3.0%	0.2%	0.6%	-0.6%	-0.7%	-1.4% +	0.5%	-1.1%	-0.8%
	(1.9%)	(NaN)	(2.1%)	(NaN)	(3627236.8%)	(0.7%)	(1.2%)	(NaN)	(0.2%)
viol_proven	1.6%	0.6%	-1.1%	-1.8%	3.2%	-0.1%	0.3%	-1.4%	-0.6%
	(2.8%)	(NaN)	(1.9%)	(NaN)	(20089311.5%)	(1.0%)	(2.4%)	(NaN)	(0.3%)
weekend	-4.2%	5.6%	-14.8% *	-5.1%	-4.8%	-13.9% ***	-4.5%	-1.3%	-3.2%
	(3.9%)	(NaN)	(5.9%)	(NaN)	(102678703.2%)	(2.8%)	(5.6%)	(NaN)	(1.1%)
age_cat25-34									-4.7%
									(0.9%)
age_cat35-44									-4.6%
									(0.9%)
age_cat45-54									-2.0%
									(1.0%)
age_cat55-64									-0.9%
									(1.7%)
age_cat65+									6.0%
									(3.4%)
N	788	604	441	902	552	1,909	502	4,693	24,338

Note. + < 0.1, * p <. 05, ** p <. 01, *** p < .001., NaN stands for Not A Number and means that the value could not be estimated.