The Impact of Field Court Attendance Notices on Property Crime in New South Wales, Australia

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Abstract

Objectives

This paper investigates the impact of Field Court Attendance Notices (FCANs) on rates of property crime in New South Wales (NSW), Australia. FCANs are used for relatively minor offenses, are issued 'on the spot', and provide an alternative to the time consuming process of arresting an alleged offender and taking them to the police station for processing. Despite their use in NSW for over 20 years, this study is the first to evaluate their impact on crime.

Methods

We use data provided by the NSW Bureau of Crime Statistics and Research, and the Australian Bureau of Statistics. We specify a general dynamic panel data model estimated via the Arellano and Bond (1991) estimator, specifically the first-differenced twostep generalised method of moments (GMM) estimator.

Results

For property crime as a whole, in both the short- and long-run, we find no significant relationship between the use of FCANS and levels of offending. However, when offending rates are disaggregated into 11 sub-categories, we find that in the short-run an increase in the use of FCANs leads to statistically significant decreases in the rate of crime for five of the sub-categories offenses considered (break and enter dwelling; motor vehicle theft; steal from motor vehicle; steal from retail store and; steal from dwelling). The long-run results are largely consistent with the short-run results in terms of their signs and statistical significance, suggesting that the effects persist.

Conclusions

The empirical analysis presented in this paper suggests that the use of FCANs is an effective and potentially efficient policing strategy for a subset of property offenses, in that offenders can be processed at lower cost and long-run rates of certain crimes reduced.

INTRODUCTION

There exists a range of strategies in the policing toolbox and the evaluation of their effectiveness continues to be of primary interest to police, scholars and policy makers. As discussed in more detail below, different police practices can vary along a number of dimensions that differentiate, for example, what is done and by whom. Like anything else, the types of strategies that are employed by the police and those that are evaluated varies over time as approaches fall into and out of favor. For example, in the 1970s, attention was given to studying the effects of random patrols, while more recently, research conducted in the United States (U.S.) and elsewhere has focused on the effectiveness of geographically focused patrol strategies at high crime places – hotspots policing (e.g. Ratcliffe et al., 2011; Braga et al., 2012).

In this article we focus on a policing strategy that, as far as we are aware, has not been implemented in the U.S. but has been employed in New South Wales (NSW), Australia over the past 20 years - Field Court Attendance Notices (FCANs). FCANs provide an alternative to arresting an alleged offender and taking them to the police station for processing. They are issued at a police officer's discretion and are generally used for relatively minor offences such as shoplifting and petty theft. FCANs are issued 'on the spot' and provide the accused with details of the alleged offense, a date and time they are required to appear at court, and the consequences of failing to attend. In other words, distinct from other policing strategies that specifically target minor offenses (e.g. removal of graffiti, aggressive use of ticketing for ordinance violations and expanded use of arrest authority), FCANs involve the use of a summons for an alleged misdemeanor (e.g. petty theft or possession of narcotics) which implies the presence of probable cause that under certain circumstances would culminate in an arrest, but instead results in a summons to court. Relative to other strategies, FCANs have two aims. The first is to allow the police to quickly and efficiently process alleged offenders, thus freeing up police time and resources. The second concerns the use of police powers of arrest. From the perspective of the courts, arrest for the majority of people is equivalent to an additional penalty and should only be used as a last resort, particularly for minor offenses. Moreover, when applied inappropriately, the use of police powers of arrest can impact negatively upon public perceptions of police legitimacy (Feerick, 2004). The use of FCANs – which do not involve an arrest - is intended to alleviate these two concerns.

Although the use of FCANs may be efficient with respect to the processing of offenders, it is of course important to know whether the process is effective in reducing both short- and long-term offending, and for which types of offenses FCANs are most suited. This study addresses these important policing questions for property crimes. Property crime was selected because this type of crime accounts for a large proportion of those offenses for which FCANs are applied and because many of the other offense categories (e.g. disorderly conduct, drug offenses) to which FCANs could be applied are rarely reported to police; rather they are usually discovered by them. From an evaluation perspective, the problem with these latter offenses is that changes in the rate at which they are recorded may more accurately reflect changes in police activity than changes in the absolute level at which offenses occur. For the purposes of illustration, Appendix A shows the frequency with which FCANs have been applied for different types of offenses in NSW since the inception of their use.

This study is unique in that it provides empirical evidence regarding the impact of a policing process intended to facilitate the more efficient processing of offenders that, despite being implemented for over twenty years in Australia, has yet to be evaluated. Its evaluation is important as the strategy represents an additional option in the policing toolkit, and if found effective might be worth testing in other countries, including the U.S. The paper proceeds as follows. A brief discussion is provided of different types of police strategies, which is followed by a discussion of the theories that underpin the use of FCANs. The data used and the method employed are then discussed. Finally, the results and their implications for policing and policy are discussed.

POLICING STRATEGIES

The policing literature identifies a number of alternative policing strategies. These include the standard model of policing (for a discussion, see Weisburd & Eck, 2004), community policing (e.g. Skogan & Hartnett, 1997), broken windows policing (Wilson & Kelling, 1982), hot spots policing (Sherman & Weisburd, 1995) and problem-orientated policing (Goldstein, 1990).

The standard model employs strategies that involve enforcing the law primarily in a reactive way. Strategies include increased number of police officers on the beat, the use of random motorized patrols to create a perception of police presence in public spaces, rapid response to calls for service intended to increase the likelihood of catching the offender, follow up investigations by detectives to enhance the chance of solving crimes, and arrest policies designed to deter and punish offenders as well as deter the general public from committing crimes. There is surprisingly limited research on the effectiveness of these strategies; however, the available evidence suggests that they tend to have limited effects on crime rates (Skogan & Frydl, 2004; Sherman et al., 1997; Weisburd & Eck, 2004).

Broken windows policing (Wilson & Kelling, 1982) represents a variant of the standard model. It is based on the theory that in communities where disorderly conduct and minor offenses (for example, public urination, fare skipping, shoplifting) go unchallenged, this sends a signal to offenders that crime is tolerated, which leads to a spiral of decline, which includes an increase in the severity of the offenses committed. Broken windows policing, which typically involves the strict and rapid arrest of those involved in minor offenses and disorder, is intended to reverse this process, sending a signal that crime will not be tolerated, no matter how small. Despite its perceived success, results examining the effectiveness of this approach are mixed and a recent systematic review of the effects of disorder policing (Braga et al., 2015) found no overall effect of aggressive (broken windows) policing strategies on crime and disorder. Interestingly, the same review did find that alternative forms of disorder policing - namely community and problem oriented policing strategies - reduced crime.

These latter approaches differ from the standard model and broken windows policing in a number of important ways. The first approach explicitly involves the community in policing, while problem solving (Goldstein, 1990) involves efforts to identify and address recurring problems and working with those (actors or agencies) with the competency to address them (whoever they might be). In their review of policing interventions and their impact on crime, Weisburd and Eck (2004) provide a useful typology for conceptualising different strategies. Their typology uses two dimensions to differentiate between the level of focus of the strategy, and the diversity of the practices employed. Strategies that are applied uniformly across a city or offenders score low in terms of their level of focus, while those that are more focused, such as (geographically focused) hotspots policing score highly. Strategies that rely on police responses alone score low on the diversity dimension. In contrast, those that engage the community in a model of co-production, or engage in problem solving with a range of agencies to address environmental (or other) conditions that make crime more likely, would score high on the diversity dimension.

The standard and broken windows models of policing require little interaction with other agencies and are not geographically focused. As such, they are located in one corner of Weisburd and Eck’s (2004) policing typology. The FCANs model also occupies this quadrant, but importantly differs from these two approaches. Before articulating why more explicitly, a brief discussion of economic theory is apposite since this underpins these approaches.

Becker's (1968) rational choice theory of crime postulates that individuals engage in criminal behavior because the expected benefits exceed the expected costs. According to Becker, the optimal amount of enforcement is dependent on, among other things, the cost of catching and convicting offenders, the nature of punishment (e.g. fines or prison terms), and the response of offenders to changes in enforcement. Becker demonstrated that: (1) optimal policies to combat illegal behavior are part of an optimal allocation of resources; (2) some punishments incorporate non-monetary costs to society and to offenders; and (3) crime, and the control of crime, are choices that can be modelled using the standard labor economics model of individual decision-making regarding the allocation of time. In short, crime is simply another choice, akin to making a decision to work or invest in education.

Similar to Becker, Stigler (1970) states that: "…the commission of offences will be an act of production for income [such as theft and smuggling] or an act of consumption [for example speeding in a car for recreation or fun]" (p.529). Further, "…he [the offender] will recon the present value of the expected returns and costs of the criminal activity and compare their difference with the net returns from other criminal activities and from legitimate activities" (p.530). In short, according to both Becker and Stigler, the rational offender considers the benefit of the illegal act alongside the risk of apprehension, conviction and the severity of punishment. As such, offender decision making should be amenable to manipulation through changes (perceived or actual) in these latter factors.

As modelled by Ehrlich (1973), the expected utility from criminal activity is a function of: the probability of arrest (P_A); the probability of conviction given arrest ($P_{C|A}$); the probability of imprisonment given conviction ($P_{I|C}$); and the average prison term (S) if imprisoned (the severity of punishment). In his review of the deterrence literature, Nagin (2013) concludes (like many others) that it is the certainty, rather than the severity of punishment that has the largest deterrent effect on offending. Because $P_A > P_{C|A} > P_{I|C}$, policies that target the probability of arrest and conviction are seen to be more effective in deterring criminal activity than policies focusing on the probability of imprisonment. As Nagin (2013) puts it "the conclusion that certainty not severity is the more effective deterrent is more precisely stated as *certainty of apprehension* and not the severity of the legal consequence ensuing from apprehension is the more effective deterrent" (p. 202). Considering the role of the police, Nagin (2013) suggests they fulfil at least two roles. The first is acting as *sentinels* whose presence is intended to deter crime. The second is acting as *apprehension agents* whose role is to catch offenders when deterrence fails (see Nagin, 2013).

The use of FCANs is intended to increase the effectiveness of law enforcement in two ways. First, like broken windows policing, swift action on the part of the police is intended to increase offender perception of the certainty with which unlawful activity will be detected *and* have potential consequences (essentially P_A). However, unlike broken windows policing, by not involving a formal arrest, police encounters with alleged offenders are (also) swift and do not in and of themselves result in a legal penalty without due process. As a consequence, relative to the use of on the spot arrests (which themselves represent a penalty), the approach has the potential to improve public perception of police legitimacy and procedural justice (e.g. Tyler, 2014). This is an important goal in its own right, but research also suggests that those (citizens, victims and offenders) who perceive they have been treated fairly by the police are more likely to cooperate with them and comply with the law in the longer-term (for a review, see Skogan & Frydl, 2004). In this sense, the use of FCANs has the potential to improve public perception of police encounters than do other more aggressive types of disorder policing. Second, the use of FCANs reduces the opportunity cost associated with the apprehension of offenders. This simultaneously increases the time the police have available to fulfill their role as sentinels, and where deterrence fails, the number of offenders they can proceed against, which has the potential to meaningfully influence offender perception of the risk of apprehension.

The aim of the current study is to test the impact of FCANs on crime. Specifically, we employ a quasi-experimental panel data design (drawing on a dataset of crime records collected in naturalistic settings) to uncover whether FCANs have a positive or negative effect on the rate of crime in the short- and long-term.

DATA AND METHOD

This study uses crime data provided by the NSW Bureau of Crime Statistics and Research (BOCSAR), and unemployment and population data provided by the Australian Bureau of Statistics (ABS). BOCSAR data are provided for 153 Local Government Areas (LGAs), defined using 2006 boundaries, throughout NSW and Norfolk Island for the years 1995 to 2013. The population mean (median) for the LGAs in the sample is 43,701 people (20,550). The mean (median) area of the LGAs in the sample is 5,171.62 km^2 (2,692.68 km^2). ABS data is for the Census years 1996, 2001, 2006 and 2011.

DEPENDENT VARIABLES

Twelve primary dependent variables representing rates of property crime are employed in our analysis. Each rate is the number of incidents reported to police in the LGA in that year, divided by the number of people in the LGA. In addition to an overall rate of property crime, the data are disaggregated according to the following sub categories of offenses: break and enter dwelling; break and enter non-dwelling; receiving or handling stolen goods; motor vehicle theft; theft from motor vehicle; theft from retail store; theft from a dwelling; theft from person; stock theft; fraud; and other theft. Table 1 provides descriptive statistics for these variables.

INSERT TABLE 1 HERE

INDEPENDENT VARIABLES

There are three independent variables: (1) Proceed FCAN – this is proportion of the total number of reported offenses (by category of offense) in the LGA for which an FCAN was used; (2) Narcotics – this is the number of persons of interest proceeded against by any means for possession and/or use of narcotics in the LGA per 1,000 persons in the LGA. This variable is included in the model in order to distinguish the impact of FCANs on offending rates from other potential confounders. This variable was used as evidence indicates that narcotic use is linked to the rise and fall in burglary and robbery in NSW (Donnelly, Weatherburn, & Chilvers, 2004; Moffatt, Weatherburn, & Donnelly, 2005); and (3) Unemployment – this is obtained from the ABS for the Census years 1996, 2001, 2006 and 2011. Time periods in between the Census years are interpolated by incorporating information from national level movements in the unemployment rate. This variable is included in an effort to control for LGA specific time varying socio-economic characteristics that may confound the influence of FCANs on the rates of crime.

THE MODEL

To investigate the impact of FCANs (compared to other forms of proceeding against persons of interest) on rates of theft, similar to Wan, Moffatt, Jones, and Weatherburn (2012), we specify the following general dynamic panel data model:

$$\ln(\mathrm{crime}_{k,t}) = \omega + \sum_{1}^{m} \alpha_m \ln(\mathrm{crime}_{k,t-m}) + \beta_1 \ln(\mathrm{proceed\_FCAN}_{k,t}) + \beta_2 \ln(\mathrm{narcotics}_{k,t}) + \beta_3 \ln(\mathrm{unemployment}_{k,t}) + \kappa_k + \sum_{1}^{t} d_t \tau_t + \varepsilon_{k,t} \quad (1)$$

Where the dependent variable ($\ln(\mathrm{crime}_{k,t})$) is the natural log of the crime rate for a particular category of crime in LGA *k*, in year *t*. ω is a general constant. The explanatory variables are: $\ln(\mathrm{crime}_{k,t-m})$ - the *m*th lag of the natural log of the crime rate, which is used to capture the dynamic nature of the process, in particular, how the effect of FCANs (compared to other forms of proceeding against persons of interest) is distributed over time; $\ln(\mathrm{proceed\_FCAN}_{k,t})$ - the natural log of the rate of incidents proceeded against by way of an FCAN; $\ln(\mathrm{narcotics}_{k,t})$ - the natural log of the arrest rate for possession and/or use of narcotics; and $\ln(\mathrm{unemployment}_{k,t})$ - the natural log of the unemployment rate in the LGA. Finally, κ_k denotes LGA specific fixed effects,[1] which are used to abstract from the effects of time-stable unmeasured factors that vary across LGAs (or in econometric language, time-invariant unobservable factors), d_t is the coefficient for the dummy variables 1 through to t; τ_t denotes time (year) fixed effects and $\varepsilon_{k,t}$ is the error term. Natural logs of all variables are used to address skewness. Conveniently, this transformation allows the coefficients to be interpreted as elasticities – that is, how responsive the crime rate is (estimated to be) to changes in the volume of FCANs per person of interest proceeded against.

Distinct from Kelaher and Sarafidis (2011) and Wan et al. (2012), in Equation 1 we do not partial out the specific probabilities of imprisonment and the average non-parole period. Hence, the coefficients of the FCAN variable should be interpreted in terms of the cumulative deterrent effects of proceeding against a person of interest by way of an FCAN, including the attendant effect of the probability of apprehension, conviction (these two are

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[1] The use of LGA-specific fixed effects differs in an important way from a hierarchical linear model with random intercepts or a random effects model in that it does not rely on the assumption that the explanatory variables are not correlated with LGA-specific component of the error term. If this assumption is violated this would bias the coefficient estimates.

arguably synonymous, with 92% of those charged with a criminal offence being convicted (Wan et al., 2012), imprisonment and sentence served.

In addition to LGA fixed effects, time fixed effects are also included in the model. The latter capture potential cross-sectional dependence (shocks common to all individuals at a point in time). The inclusion of time fixed effects is particularly important as the autocorrelation test and the robust estimates of the coefficient standard errors, on which the dynamic panel data model crucially relies, assume no correlation across LGAs in the idiosyncratic disturbances. Time fixed effects make this assumption more likely to hold (Roodman, 2009).

THE ESTIMATION TECHNIQUE

The estimation technique employed for the dynamic panel data model specified in Equation 1 is the Arellano and Bond (1991) estimator, specifically the first-differenced (as indicated by the Δ symbol) twostep generalized method of moments (GMM) estimator depicted in Equation 2:

$$\Delta \ln(\mathrm{crime}_{k,t}) = \sum_{1}^{m} \alpha_m \Delta \ln(\mathrm{crime}_{k,t-m}) + \gamma_1 \Delta \ln(\mathrm{proceed\_FCAN}_{k,t}) + \gamma_2 \Delta \ln(\mathrm{narcotics}_{k,t}) + \gamma_3 \Delta \ln(\mathrm{unemployment}_{k,t}) + \sum_{1}^{t} d_t \Delta \tau_t + \Delta \varepsilon_{k,t} \quad (2)$$

Where all variables are defined as in Equation 1. Note, however, that the constant term (ω) is transformed out in first differenced-GMM. The implementation of this estimator is the ideal vehicle for testing causal claims about the criminal justice system on the property crime rate as it is possible to distinguish the temporal order of events. This technique ameliorates the problems that result from having endogenous explanatory variables. As noted by Wan et al. (2012) this estimator mitigates the risk of omitted variables, simultaneity,[2] ratio bias and it avoids full specification of the serial correlation and heteroscedasticity properties of the error.

It is also worth noting that while the twostep GMM estimator is more efficient than the onestep 2SLS estimator, the first-differenced GMM is more conservative than the system GMM.[3] However, the standard errors are severely downwardly biased in finite samples. To remedy this, robust Windmeijer-corrected standard errors are reported (Cameron & Trivedi, 2010; Roodman, 2009; Windmeijer, 2005). Moreover, orthogonal deviations (Arellano & Bover, 1995) and the small sample size correction (Cameron, Gelbach, & Miller, 2011) are employed. A number of diagnostic checks and procedures are also used to ensure the appropriateness of the models estimated.

DIAGNOSTIC CHECKS

To begin, in Equation 2, all explanatory variables (except for the time fixed effects) are treated as endogenous or predetermined. Importantly, the Arellano-Bond estimator used in

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[2] Simultaneity bias arises from the construction of the dependent variable ($\ln(\mathrm{crime}_{k,t})$) and the explanatory variables ($\ln(\mathrm{crime}_{k,t-m})$) and ($\ln(\mathrm{proceed\_FCAN}_{k,t})$), where reported crimes feature in the numerator of the crime rate variables and the denominator of the FCAN variable.

[3] The first-difference GMM is more conservative as, unlike the system-GMM, it does not rely on the assumption that the first differences in the instrumenting variables are not correlated with the LGA-specific fixed effects (Roodman, 2009). For our study it is reasonable to expect, consistent with the 'Broken Windows' hypothesis (Wagers, Sousa, & Kelling, 2008), that a stable and higher than average level of crime in an area and associated stigmatisation may be related to past changes in the crime rate in that area. For this reason, there are strong theoretical grounds for employing the first-differenced GMM rather than the system-GMM. Also, ratio bias might arise due to measurement error owing to a systematic bias in how crimes and arrests are reported to, and recorded by, law enforcement agencies. In two key respects the use of the first-differenced twostep GMM estimator addresses these concerns. First, where these sources of measurement error are time-invariant they are abstracted from through first-differencing. Second, where these sources of measurement error are non-random and time varying, the use of valid instruments makes consistent estimation possible (Bond, Hoeffler, & Temple, 2001). Moreover, the satisfaction of the exclusion restriction criteria provides assurance that the results are not confounded by measurement error even where the measurement error may be decidedly non-random.

this study employs ‘internal’ instruments for the endogenous variables. These instruments are lags of the independent variables.[4] For example, the $\ln(\mathrm{crime}_{\mathrm{kt}-1})$ variable in column 1 of Table 3a is instrumented using its own lags, specifically, the 1st order lag, the 2nd order lag and the 3rd order lag. The Hansen test of overriding restrictions is used to test whether or not the instruments themselves are endogenous. In addition to this test of the exclusion restriction, consistent estimation of the Arellano-Bond estimator also requires that the error term be serially uncorrelated. This assumption and requirement is testable using the Arellano-Bond test which tests the null hypothesis that there is no correlation:

- Between the first differenced contemporaneous error term ($\Delta\varepsilon_{\mathrm{k,t}}$) and the first differenced error in t-1 ($\Delta\varepsilon_{\mathrm{k,t-1}}$) (as indicated by AR(1));
- Between first differenced contemporaneous error term ($\Delta\varepsilon_{\mathrm{k,t}}$) and the first differenced error in t-2 ($\Delta\varepsilon_{\mathrm{k,t-2}}$) (as indicated by AR(2)); and
- Between the first differenced contemporaneous error term ($\Delta\varepsilon_{\mathrm{k,t}}$) and the first differenced error in t-3 ($\Delta\varepsilon_{\mathrm{k,t-3}}$) (as indicated by AR(3)).

AR(1) Prob > z = 0.0000

AR(2) Prob > z = 0.9240

AR(3) Prob > z = 0.6310

Note, we expect to reject the null hypothesis at the first order AR(1) as:$Cov(\Delta\varepsilon_{\mathrm{k,t}}, \Delta\varepsilon_{\mathrm{k,t-1}}) = Cov(\varepsilon_{\mathrm{k,t}} - \varepsilon_{\mathrm{k,t-1}}, \varepsilon_{\mathrm{k,t-1}} - \varepsilon_{\mathrm{k,t-2}}) = -Cov(\varepsilon_{\mathrm{k,t}} - \varepsilon_{\mathrm{k,t-1}}, \varepsilon_{\mathrm{k,t-1}} -$

[4] An instrumental variable (IV) is an exogenous variable correlated with an endogenous explanatory (or independent) variable, although not correlated with the dependent variable except through the IV’s correlation with the endogenous explanatory variable. An IV is used to estimate causal relationships where the explanatory variables are correlated with the error term. Importantly, there are two main requirements for using an IV. First, the IV must be correlated with the endogenous explanatory variable(s). Second, the IV cannot be correlated with the error term in the explanatory equation. In both instances this is conditional on the other covariates.

$\varepsilon_{\mathrm{k,t-2}}) \neq 0$. But we do not expect it to be rejected at higher orders ($\Delta\varepsilon_{\mathrm{k,t}}$ will not be correlated with $\Delta\varepsilon_{\mathrm{k,t-s}}$ for $s \geq 2$). The results in column 1 of Table 3a indicate that there is no serial correlation in the original error $\Delta\varepsilon_{\mathrm{k,t}}$, as desired. In the estimated models, the number of autoregressive terms or lags was determined by statistical significance, the Arellano and Bond (1991) test for zero autocorrelation in the first-differenced errors and satisfaction of the exclusion restriction.

A potential pitfall associated with the use of the Arellano-Bond estimator is the problem of instrument proliferation. That is, the Arellano-Bond estimator may generate many internal instruments. For example, where the $\ln(\mathrm{proceed\_FCAN_{k,t}})$ variable is instrumented using its own lags (specifically, the $(\ln(proceed\_FCAN_{k,t-1})$ (1st order lag), $(\ln(proceed\_FCAN_{k,t-2})$ (2nd order lag) and $(\ln(proceed\_FCAN_{k,t-3})$ (3rd order lag). In t = 3 only the first two of these are available. In t = 4, 5 and 6 all three are available yielding a total of 2 + 3 + 3 + 3 = 11 instruments over t = 4 to t = 6 alone and for the FCAN variable alone. Each instrumenting variable generates one column for each time period and lag available to that time period making the number of instruments quadratic in T. In order to address this proliferation of instruments, the instruments may be ‘collapsed’. This stacks these instruments in long form. For example,

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ y_i1 & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & y_i2 & y_i1 & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & y_i3 & y_i2 & y_i1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \text{or, collapsed} \begin{bmatrix} 0 & 0 & 0 & \cdots \\ y_i1 & 0 & 0 & \cdots \\ y_i2 & y_i1 & 0 & \cdots \\ y_i3 & y_i2 & y_i1 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

In doing so, we are able to guard against instrument proliferation that would otherwise weaken the Hansen test (for example, you could get implausibly good *p* values of 1.0000), which, while robust to heteroscedasticity and autocorrelation, is not robust to instrument proliferation. The use of too many instruments would fail to expunge the endogeneity through overfitting. For intuition, consider that 2SLS, if the number of instruments equals the number of observations, the R^2 of the first-stage regressions are 1 and the second-stage results match those of (biased) OLS. The use of the collapse option helps to address this problem (Roodman, 2009). For example, in column 1 of Table 3a (discussed in full later) without collapsing the instruments 221 are generated. In contrast when the instruments are collapsed the instrument count is only 29.

Additional measures were taken to interrogate the appropriateness of the model. Specifically, a simple least squares dummy variable estimation confirmed that the LGA fixed effects are jointly statistically significant. Further, Wooldridge's (2010) test for serial correlation provided evidence of first-order autocorrelation in all categories of offending. This result demonstrates the dynamic nature of the data. Moreover, Im, Pesaran and Shin's (2003) test for unit roots in panel data, after abstracting from cross-sectional dependence (removing cross-sectional means), indicates that all dependent variables are stationary. These findings attest to the appropriateness of using the first-differenced twostep GMM estimator.

As a final check regarding the plausibility of the lag term coefficient estimates, these estimates are compared with those obtained using a pooled OLS model and a traditional fixed effects model. These terms describe the speed with which impacts are distributed over time, where smaller coefficients and lower order lags indicate a more rapid change, and larger coefficients and higher order lags indicate a more gradual change, over time. The lag term estimates should be between the pooled OLS model (the upper bound, as the estimates are biased upwards) and the traditional fixed effects model (the lower bound, as the estimates are biased downwards). All the models are within the bounds.

SHORT-RUN AND LONG-RUN IMPACTS OF FCANS

Results for rates of crime are presented with respect to their short- and long-run effects. The short-run effect refers to changes that occur in a given period (in this study, each year). The long-run effect, also known as the total or asymptotic effect, encompasses the entire distributive process; it includes (in addition to the short-run effect) the impact of the variables in previous periods through the lag term(s).

A priori, it is expected that the lag terms, individually, will be less than unity although greater than zero and sum to less than one to ensure stationarity. After holding other factors constant, the short-run effects (the coefficients) γ_1 may be expected to be positive if greater use of FCANs encourages offending (or conversely other means of proceeding against discourages offending). It is possible that being issued a FCAN, rather than being proceeded against by other means, may provide less of a deterrent. This is quite plausible for more violent offenses. For example, Kelaher and Sarafidis (2011) find that violent offenders are more persistent and resistant to deterrence. It may also be the case, however, that for relatively minor offences or economically motivated crimes, the use of FCANs enables law enforcement officers to increase capture rates, thus creating a larger deterrent effect, *ceteris paribus*. This would translate to a negative coefficient for γ_1. With regards to the other determinants of the crime rate, the coefficients γ_2 and γ_3 are expected to be positive.

The short-term effects illustrated by the coefficient estimates γ_1 through to γ_3 only point to a fraction of the asymptotic effect that is distributed over time.

In order to estimate the total long-run effect on the crime rate, Equation 3 is employed:

$$\Delta \mathrm{crime}_{\mathrm{k,t}} = \frac{\gamma_{\mathrm{j}}}{1-\sum_{1}^{m}\alpha_m}, \qquad \mathrm{j} = 1,\ldots,4 \qquad \mathrm{m} = 1,\ldots,2 \tag{3}$$

Where the sum of the lag term(s) (α_m) is less than one and greater than zero within the bounds of stationarity. The magnitude of this coefficient determines the degree to which the effect of FCANs is distributed over the short- compared to the long-run. The long-run cumulative effect can be expected to be greater than the short-run effect.

RESULTS

A simple examination of the pairwise contemporaneous correlations are illustrated in Table 2. Results show that in some cases the correlation between variables is relatively high. The highest correlations are 0.5724 (for motor vehicle theft, between ln(narcotics) and ln(crime)), 0.3982 (for steal from person, between ln(narcotics) and ln(crime)) and 0.3978 (for stealing, between ln(narcotics) and ln(crime)). They are all at the upper bounds of an acceptable level, nonetheless we feel that correlations between variables have not adversely affected results and we are, therefore, confident in the estimates presented in the following sections.[5]

INSERT TABLE 2 HERE

[5] Variance inflation factors were also investigated. This is a significant hurdle for models which include lag(s) of the dependent variable. All models except the 'Motor vehicle theft' model have variance inflation factors that are less than the rule of thumb of 10. For this model the highest variance inflation factor is found for the second order lag of 'Motor vehicle theft', which is marginally higher than 10 at 11.1900. O'Brien (2007) shows that even variance inflation factors well over 10 are not necessarily a serious problem. Multicollinearity does not bias coefficient or standard error estimates, it simply increases standard errors relative to instances with low collinearity. Larger standard errors, of course, make it harder to reject the null hypothesis and can explain null findings. Nonetheless, it does not appear that our models are especially affected by multicollinearity. The magnitude, signs and levels of statistical significance for the short-term effect do not change greatly for the omission of this lag term. This likely reflects the fact that the variance inflation factor only marginally exceeds the conventional limit.

EMPIRICAL RESULTS

In Tables 3 (a and b) and 4 (a and b) we report the short-run and long-run results for rates of property crime.[6] We reiterate that the impact of the FCAN variable is interpreted as the impact of the use of FCANs to proceed against persons of interest as either reducing or increasing the crime rates through deterrence (or lack thereof), compared to other means of proceeding.

INSERT TABLE 3a and 3b HERE

OFFENCE RATES IN THE SHORT-RUN

Tables 3a and 3b provide an abridged summary of short-run model results for rates of overall property crime and the 11 sub-categories of offending considered. Full results are presented as Tables B1 and B2 in Appendix B. As indicated in Table 3a (column 1), we did not find a statistically significant association between the use of FCANs and overall property offences at the 5% level (p-value of 0.0760). In terms of the distributed process itself, it is best described by a first order, second order and fourth order lag. These coefficient estimates are stationary and are not statistically significantly different from equivalent pooled ordinary least squares estimates (which are biased upwards) and greater than similar fixed effects

[6] The reader should note that crime categories 9 (Steal from person) and 10 (Stock theft) contain a number of zeros, which before being logged are linearly transformed by adding a constant of 1 (a typical approach employed to deal with zero values in this context). Results for these categories therefore have the potential to be biased with the strength of the relationship between the use of FCANs and crime rates in these categories being understated. All other categories do not have this problem. One way of addressing this is to take the square root of the variable. However, this requires the reader to use the chain rule to interpret the results – this is complex and not widely understood, making interpretation of the results more difficult. The use of natural log allows a more straightforward interpretation of the results and permits the estimation of a flexible functional form. For completeness, we analyzed the data using a square root transformation (results available upon request) but as the results did not differ materially (but are harder to interpret) to those reported we discuss them no further.

estimates (which are biased downwards). The lag terms of all subsequent regression estimates fall neatly within the bounds suggested by these models.

In regards to sub-categories 2, 5, 6, 7 and 8, the results indicate that a 1% increase in the use of FCANs reduces offenses by between 0.05% (sub-category 7) and 14.72% (sub-category 6). No statistically significant relationship could be found between the use of FCANs and offense rates for offense sub-categories 3, 4, 9, 10, 11 and 12. The coefficient estimates are stationary, and the lag term coefficient estimates fall within the bounds of equivalent pooled ordinary least squares estimates and fixed effects estimates.

In regards to the effect of the arrest rate for the possession and use of narcotics, a strong positive association is found between this variable and stealing sub-categories 4, 7 and 11. In regards to the rate of unemployment, a positive association is found between this variable and stealing sub-categories 5 and 7.

Our F-test results suggest that all models are jointly statistically significant at the 1% level and the Arellano and Bond test provides no evidence of autocorrelation at AR(2) and AR(3). Further, the Hansen test of over identifying restrictions is not rejected in any model. Not rejecting the Hansen test of overriding restrictions is important. It means that the instruments themselves are not endogenous (they are exogenous). That is, they do not explain the dependent variable except through the independent variables that they are instrumenting.

THE LONG-RUN IMPACT OF FCANS ON OFFENSE RATES

Tables 4a and 4b provide long-run model results. Table 4a (column 1) suggests that the use of FCANs does not deter property offenses in the aggregate. However, in the long-run, as illustrated in Tables 4a and 4b, the use of FCANs has a statistically significant negative long-run effect on the rates of offenses for sub-categories 5, 7 and 8. No significant relationship is found for the other sub-categories.

INSERT TABLE 4a and 4b HERE

DISCUSSION

The aim of this study was to estimate the impact of FCANs on overall rates of property offenses and for 11 specific types of offenses. In both the short- and long-run, at the 5% level we find no statistically significant effect between the use of FCANs and the overall level of property offenses. Considering the sub-categories of offenses, in the short-run, with the exception of the offense receiving stolen goods, the directions of the estimated coefficients are consistent with the idea that FCANs have a deterrent effect on specific types of crime. These effects are statistically significant for five of the 11 sub-categories of offenses (break and enter dwelling; motor vehicle theft; steal from motor vehicle; steal from retail store and; steal from dwelling). Setting statistical significance aside for one moment, one reason for the anomalous finding for the offense receiving stolen goods is perhaps that, unlike the other offenses, this is not a direct contact crime, and offenders may perceive the likelihood of detection as lower for this than for other types of offenses.

The long-run results are largely consistent with the short-run results. That is, in the long-run, our results show that an increase in the use of FCANs leads to statistically significant decreases in the rate of crime for the following sub-categories of offenses: motor vehicle theft; steal from retail store; and steal from dwelling.

The empirical analysis presented above thus suggests that for some categories of offenses, the use of FCANs may be an effective and potentially efficient policing strategy in that, compared to alternative approaches of proceeding, offenders can be processed at lower cost and long-run rates of crime reduced. However, it would appear that the effects are specific rather than generalized, since the effects were observed only for some forms of crime, both in the short- and long-term, and overall property crime did not appear to be affected. Thus, contrary to the ideas that underpin Broken Windows policing, the use of FCANs did not appear to have a general deterrent effect on property crime. If replicated elsewhere, this finding suggests that rather than being applied universally across crime types, the use of FCANs should be targeted to address specific types of crime. While it was not possible to do this in the current study, unpicking why FCANs appear to impact upon some forms of (minor) crime but not others would seem to be a useful next step.

Continuing with the theme of specificity, as noted in the introduction, in NSW FCANs are applied uniformly across geographic locations. The absence of a geographic focus to this strategy contrasts with contemporary initiatives in the U.S. and other countries where hotspots policing is currently enjoying popularity (e.g. Braga et al., 2015). The aim of hotspots policing is to direct resources to those locations where the likelihood of crime is highest. As such, the targeting strategy is intended to increase the frequency with which police officers will be present during the commission of a crime (or better still) before it occurs, increasing the likelihood that they will detect or (more likely) deter it. In this way, the targeting strategy can be seen to increase the dosage of police officer presence at locations where crime is most likely. The use of FCANs also effectively influences dosage. That is, through their swift administration (relative to arrests) FCANs increase the amount of time that police officers are available to act as sentinels or guardians against crime. An obvious evolution that might be tested in future research would be to combine the use of FCANs and a hotspots policing strategy.

A further issue discussed in the introduction concerned procedural justice and police legitimacy. We noted that, relative to more aggressive disorder policing strategies, the process through which FCANs are issued may well increase public - and indeed offender (see Skogan & Frydl, 2004) - perceptions of police legitimacy, and as a consequence influence their compliance with the law. It was beyond the scope of the current study to examine this issue here, but future research might examine (for example) public perceptions of police legitimacy for encounters that involve the issuance of FCANs as opposed to those that involve the arrest of offenders (for similar offenses).

This study is of course not without limitations. Chief amongst these is that the data analyzed are recorded crime data that are reported to and recorded by the police. It is well documented that much crime goes unreported and so the reader should consider this when interpreting the results reported here. However, we can see no obvious reason for why this should affect the results reported, as the model specification was designed to address such issues.

An additional caveat to consider when interpreting these results is that at an individual level, it is plausible that there is some self-selection in terms of police officers' decisions regarding the use of FCANs versus other means of proceeding against persons of interest. For example, it is possible that police officers are more likely to issue FCANs to individuals who are less likely to re-offend or conversely less likely to issue FCANs to individuals who are more likely to re-offend. This decision is a result of their understanding of individuals of interest who reside or operate within their local area command. Such self-selection would exaggerate the deterrent effect. This is difficult to test using a quasi-experimental design, but future studies might do so using a randomized control trial intended to detect direct effects of the intervention and any diffusion of benefits that might arise.

This study is unique in that it provides empirical evidence regarding the use of a policing process intended to more efficiently process offenders for relatively minor crimes (specifically, property offenses). For approximately 20 years FCANs have been used by NSW police, however, the effectiveness of this has not previously been investigated. The findings reported here thus have important implications for police management who are held to account both in regards to the strategies employed to protect or enhance community safety but also the effectiveness of these strategies in terms of reductions in the overall rate of crime. Our findings suggest that for some crimes the effects of the approach are observable in the short-term but are also persistent. The approach thus represents a promising one that might be added to the police toolbox in countries other than Australia.

Future research may benefit from investigating the potentially time varying heterogeneity of the autoregressive terms. It may be the case that the distributed impacts of the use of FCANs differ over time, and may potentially reveal some interesting and useful insights in terms of the dynamic nature of the process. In our study we controlled for and abstracted from spatial/geographic/locational heterogeneity, specifically, differences between local government areas. By treating spatial/geographic/locational heterogeneity as a nuisance term, this study provides estimates independent of such contextual factors. However, this research might be extended further by exploring how the effectiveness of policing policies may depend on different spatial/geographic/locational characteristics. For instance, it may be the case that FCANs are more or less effective in areas of high/low informal surveillance. Further work may also explore the extent to which the apparent effects of the use of FCANs are due to the police being able to process offenders more quickly (i.e. their role as apprehension agents), or to their opportunity to act as sentinels whose presence deters crime.

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Table 1: Descriptive statistics for crime rates (per 100,000 population) and FCANs issued as a proportion of the total number of reported incidents or persons of interest proceeded against as defined in the crime rate (by category of offence) in the LGA[7,8]

Variable name	Observations	Mean (Std. dev.)	Min	Max
Crime rates				
Stealing	2926	0.0264 (0.0182)	0.0000	0.2941
Break and enter dwelling	2926	0.0077 (0.0056)	0.0000	0.0527
Break and enter non-dwelling	2926	0.0058 (0.0045)	0.0000	0.0480
Receiving or handling stolen goods	2926	0.0010 (0.0012)	0.0000	0.0199
Motor vehicle theft	2926	0.0036 (0.0035)	0.0000	0.0360
Steal from motor vehicle	2926	0.0075 (0.0063)	0.0000	0.0943
Steal from retail store	2926	0.0023 (0.0020)	0.0000	0.0204
Steal from dwelling	2926	0.0044 (0.0023)	0.0000	0.0226
Steal from person	2926	0.0010 (0.0026)	0.0000	0.0530
Stock theft	2926	0.0005 (0.0007)	0.0000	0.0066
Fraud	2926	0.0037 (0.0032)	0.0000	0.0503
Other theft	2926	0.0072 (0.0064)	0.0000	0.1111
Proceed_FCAN				
Stealing	2926	0.0152 (0.0207)	0.0000	0.4070
Break and enter dwelling	2907	0.0014 (0.0072)	0.0000	0.1111
Break and enter non-dwelling	2911	0.0016 (0.0103)	0.0000	0.2500
Receiving or handling stolen goods	2712	0.0798 (0.1444)	0.0000	2.0000

[7] The proceed_FCAN has a maximum outside the expected limit of one because reported incidents do not equate exactly with offences. For example, one incident may involve two offenders (New South Wales Bureau of Crime Statistics and Research, 2014).

[8] Where the minimum value is zero, the variables were linearly transformed (adding one) in order to preserve the relative ordering of the observations and permit the natural log transformation.

Motor vehicle theft	2879	0.0062 (0.0352)	0.0000	1.0000
Steal from motor vehicle	2906	0.0030 (0.0232)	0.0000	1.0000
Steal from retail store	2771	0.1238 (0.2028)	0.0000	3.5000
Steal from dwelling	2909	0.0036 (0.0164)	0.0000	0.5000
Steal from person	2453	0.0057 (0.0508)	0.0000	1.0000
Stock theft	2411	0.0027 (0.0332)	0.0000	1.0000
Fraud	2893	0.0230 (0.1257)	0.0000	5.3333
Other theft	2917	0.0093 (0.0186)	0.0000	0.3846

Table 2: Contemporaneous correlations

	ln(crime)	ln(proceed_FCAN)	ln(narcotics)	ln(unemployment)
Stealing				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0304	1.0000		
ln(narcotics)	0.3978	0.0610	1.0000	
ln(unemployment)	0.1346	0.1361	0.2651	1.0000
Break and enter dwelling	1.0000			
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0205	1.0000		
ln(narcotics)	0.3326	-0.0070	1.0000	
ln(unemployment)	0.2987	0.0559	0.2818	1.0000
Break and enter non-dwelling				
ln(crime)	1.0000			
ln(proceed_FCAN)	0.0217	1.0000		
ln(narcotics)	0.1425	0.0074	1.0000	
ln(unemployment)	0.3363	0.0531	0.2817	1.0000
Receiving or handling stolen goods				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0284	1.0000		
ln(narcotics)	0.3676	-0.0126	1.0000	
ln(unemployment)	0.1878	-0.0168	0.2748	1.0000
Motor vehicle theft				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0795	1.0000		
ln(narcotics)	0.5724	-0.0475	1.0000	
ln(unemployment)	0.1923	0.0299	0.2809	1.0000
Steal from motor vehicle				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0568	1.0000		
ln(narcotics)	0.4330	-0.0050	1.0000	
ln(unemployment)	0.1035	0.0303	0.2821	1.0000
Steal from retail store				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.1375	1.0000		
ln(narcotics)	0.3645	0.0398	1.0000	
ln(unemployment)	0.1788	0.0136	0.2734	1.0000
Steal from dwelling				

ln(crime)	1.0000			
ln(proceed_FCAN)	0.0171	1.0000		
ln(narcotics)	0.0393	-0.0001	1.0000	
ln(unemployment)	0.3313	0.0800	0.2824	1.0000
Steal from person				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0276	1.0000		
ln(narcotics)	0.3982	-0.0216	1.0000	
ln(unemployment)	-0.0108	0.0365	0.2646	1.0000
Stock theft				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0048	1.0000		
ln(narcotics)	-0.2493	-0.0057	1.0000	
ln(unemployment)	-0.1716	0.0046	0.2994	1.0000
Fraud				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0720	1.0000		
ln(narcotics)	0.2913	-0.0264	1.0000	
ln(unemployment)	-0.0341	0.0886	0.2795	1.0000
Other theft				
ln(crime)	1.0000			
ln(proceed_FCAN)	-0.0341	1.0000		
ln(narcotics)	0.3255	0.0208	1.0000	
ln(unemployment)	0.0463	0.0292	0.2819	1.0000

Table 3a: Short-run model results (offences - stealing categories 1-6)

	(1) Stealing ln(crime)	(2) Break and enter dwelling ln(crime)	(3) Break and enter non-dwelling ln(crime)	(4) Receiving/ handling stolen goods ln(crime)	(5) Motor vehicle theft ln(crime)	(6) Steal from motor vehicle ln(crime)
ln(crime) (lag 1)	0.6350*** (0.0496)	0.5875*** (0.0424)	0.4327*** (0.0562)	0.4629*** (0.1074)	0.5797*** (0.0299)	0.4964*** (0.0963)
ln(crime) (lag 2)	0.1699*** (0.0316)	0.2242*** (0.0346)	0.2416*** (0.0546)		0.1454*** (0.0300)	0.1535*** (0.0444)
ln(crime) (lag 3)			0.0663 (0.0356)		0.1639*** (0.0263)	0.0905** (0.0365)
ln(crime) (lag 4)	0.0975*** (0.0297)					
ln(proceed_FCAN)	-0.0144 (0.0080)	-0.1135** (0.0570)	-0.0597 (0.0338)	0.0008 (0.0015)	-0.0016** (0.0006)	-0.1472** (0.0639)
ln(narcotics)	0.0024 (0.0015)	0.0015 (0.0019)	0.0013 (0.0015)	0.0025*** (0.0007)	0.0004 (0.0004)	0.0025 (0.0023)
ln(unemployment)	-0.0006 (0.0014)	-0.0000 (0.0012)	0.0009 (0.0009)	0.0003 (0.0004)	0.0010** (0.0005)	-0.0000 (0.0014)
Observations	2156	2446	2297	2415	2269	2293
Groups	154	154	154	153	154	154
F-statistics	F(20, 154) = 273.1900	F(21,154)= 163.2300	F(21, 154) = 156.8800	F(21, 153) = 43.7000	F(21, 154) = 239.8900	F(21, 154) = 42.6100
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lag limits (ln(crime) (lag 1))	[1, 3]	[1,2]	[1, 2]	[1, 1]	[1, 1]	[1, 2]
Lag limits (ln(crime) (lag 2))		[1,2]	[1, 2]		[1, 1]	[1, 2]
Lag limits (ln(crime) (lag 3))			[1, 2]		[1, 1]	[1, 2]
Lag limits (other)		[2, 6]	[2, 2]	[2, 3]	[1, 2]	[2, 6]
Instrument count	29	34	22	24	24	34
Arellano-Bond tests						
AR(1) Prob > z =	0.0000	0.0000	0.0000	0.0040	0.0000	0.0380
AR(2) Prob > z =	0.9240	0.5180	0.4360	0.1780	0.6800	0.5900
AR(3) Prob > z =	0.6310	0.9430	0.5430	0.4580	0.8750	0.7790
Hansen test Prob > χ^2 =	0.6170	0.6310	0.5440	0.5950	0.8410	0.5560

Standard errors in parentheses

** $p < 0.05$, *** $p < 0.01$

Table 3b: Short-run model results (offences - stealing categories 7-12)

	(7) Steal from retail store ln(crime)	**(8) Steal from dwelling ln(crime)**	**(9) Steal from person ln(crime)**	**(10) Stock theft ln(crime)**	**(11) Fraud ln(crime)**	**(12) Other theft ln(crime)**
ln(crime) (lag 1)	0.4183^{***} (0.0538)	0.4647^{***} (0.0320)	0.9128^{**} (0.3767)	0.1663^{**} (0.0769)	0.4019^{**} (0.1590)	0.8538^{***} (0.0927)
ln(crime) (lag 2)		0.2455^{***} (0.0338)			0.2127 (0.1155)	
ln(proceed_FCAN)	-0.0005^{***} (0.0001)	-0.0028^{**} (0.0013)	-0.1705 (1.0679)	-0.0071 (0.0089)	-0.0010 (0.0007)	-0.1340 (0.2270)
ln(narcotics)	0.0006^{***} (0.0002)	0.0003 (0.0003)	-0.0049 (0.0321)	-0.0004 (0.0002)	0.0017^{**} (0.0008)	-0.0013 (0.0032)
ln(unemployment)	0.0005^{**} (0.0003)	0.0005 (0.0004)	0.0009 (0.0075)	-0.0002 (0.0004)	-0.0009 (0.0010)	0.0040 (0.0064)
Observations	2470	2450	2165	2121	2587	2610
Groups	152	154	151	150	154	154
F-statistics	F(21, 152) = 14.0200	F(21, 154) = 92.4900	F(21, 151) = 14.0100	F(21, 150) = 4.5000	F(20, 154) = 7.3800	F(21, 154) = 33.7800
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lag limits (ln(crime) (lag 1))	[1, 3]	[1, 1]	[6, 7]	[1, 1]	[2, 2]	[5, 6]
Lag limits (ln(crime) (lag 2))		[1, 1]				
Lag limits (ln(crime) (lag 3))					[2, 5]	
Lag limits (other)	[1, 3]	[1, 4]	[6, 6]	[2, 4]	[1, 2]	[2, 3]
Instrument count	29	30	22	27	26	25
Arellano-Bond tests						
AR(1) Prob > z =	0.0000	0.0000	0.8700	0.0000	0.0000	0.2510
AR(2) Prob > z =	0.9700	0.1310	0.8770	0.8590	0.0790	0.4020
AR(3) Prob > z =	0.1000	0.9310	0.7240	0.1520	0.4550	0.8360
Hansen test Prob > χ^2 =	0.2550	0.9570	0.4700	0.4340	0.3890	0.8550

Standard errors in parentheses

** $p < 0.05$, *** $p < 0.01$

Table 4a: Long-run model results (offences - stealing categories 1-6)

	(1) Stealing ln(crime)	(2) Break and enter dwelling ln(crime)	(3) Break and enter non-dwelling ln(crime)	(4) Receiving/ handling stolen goods ln(crime)	(5) Motor vehicle theft ln(crime)	(6) Steal from motor vehicle ln(crime)
ln(proceed_FCAN)	-0.1478 (0.0975)	-0.6027 (0.4035)	-0.2303 (0.1387)	0.0014 (0.0028)	-0.0139** (0.0057)	-0.5670 (0.3411)
ln(narcotics)	0.0244 (0.0196)	0.0080 (0.0084)	0.0049 (0.0058)	0.0046** (0.0018)	0.0035 (0.0034)	0.0096 (0.0087)
ln(unemployment)	-0.0057 (0.0135)	-0.0000 (0.0062)	0.0035 (0.0035)	0.0006 (0.0008)	0.0093 (0.0057)	-0.0002 (0.0053)

Delta method standard errors in parentheses

** $p < 0.05$, *** $p < 0.01$

Table 4b: Long-run model results (offences - stealing categories 7-12)

	(7) Steal from retail store ln(crime)	(8) Steal from dwelling ln(crime)	(9) Steal from person ln(crime)	(10) Stock theft ln(crime)	(11) Fraud ln(crime)	(12) Other theft ln(crime)
ln(proceed_FCAN)	-0.0008***	-0.0097**	-1.9557	-0.0085	-0.0026	-0.9165
	(0.0002)	(0.0047)	(7.4796)	(0.0107)	(0.0024)	(1.3727)
ln(narcotics)	0.0011**	0.0009	-0.0568	-0.0004	-0.0024	-0.0090
	(0.0002)	(0.0009)	(0.2985)	(0.0003)	(0.0016)	(0.0233)
ln(unemployment)	0.0009**	0.0016	0.0102	-0.0002	0.0045**	0.0272
	(0.0004)	(0.0012)	(0.1012)	(0.0005)	(0.0020)	(0.0435)

Delta method standard errors in parentheses

** $p < 0.05$, *** $p < 0.01$

Table A1: Frequency of the use of FCANs (1995-2013) – all offense categories

Year	Offense category					
	Against justice procedures	**Assault**	**Disorderly conduct**	**Drug offences**	**Malicious damage to property**	**Stealing**
1995	0	2	0	0	1	3
1996	1	16	0	0	3	15
1997	25	123	72	30	83	363
1998	405	1359	2780	1345	977	3027
1999	983	2411	6134	3542	1676	5709
2000	827	2317	4681	3240	1637	5747
2001	673	1993	3128	2997	1457	4824
2002	602	1464	2618	2230	1225	4574
2003	580	1288	2179	2457	1178	4408
2004	654	1412	2327	2691	1219	3895
2005	791	1294	2668	2706	1240	3630
2006	795	1235	2404	2853	1153	3575
2007	704	1248	2403	3066	1200	3635
2008	714	1041	1401	3767	1085	2435
2009	724	903	1350	4979	957	2546
2010	546	848	985	5006	832	2229
2011	590	883	983	5689	837	2364
2012	528	809	910	6826	765	2589
2013	508	931	941	6859	737	2437

Source: New South Wales Bureau of Crime Statistics and Research

Table A2: Frequency of the use of FCANs (1995-2013) – stealing sub-categories

Year	Offense category									
	Break and enter dwelling	**Break and enter non-dwelling**	**Receiving or handling stolen goods**	**Motor vehicle theft**	**Steal from motor vehicle**	**Steal from retail store**	**Steal from dwelling**	**Steal from person**	**Stock theft**	**Fraud**	**Other theft**
1995	0	0	5	0	0	0	2	0	0	0	1
1996	6	2	8	4	1	2	3	0	0	6	3
1997	10	12	59	14	11	205	12	2	0	107	26
1998	71	69	620	96	141	1833	156	21	6	457	413
1999	115	138	1258	162	208	3668	222	46	12	678	875
2000	102	108	1367	206	194	3720	182	32	2	720	897
2001	62	64	966	127	144	3417	159	22	1	478	603
2002	35	50	721	87	82	3383	92	27	0	535	455
2003	36	39	690	78	88	3390	100	29	5	376	420
2004	28	28	613	44	72	2973	83	11	0	331	425
2005	26	23	510	63	111	2572	71	23	0	407	446
2006	26	21	527	42	64	2655	71	18	1	347	419
2007	40	25	503	30	58	2762	45	21	2	329	418
2008	24	24	363	42	53	1781	44	20	3	252	282
2009	30	21	370	37	55	1972	47	10	2	156	305
2010	12	14	419	26	43	1669	40	15	0	176	286
2011	17	14	512	32	36	1734	40	15	2	245	293
2012	10	16	665	33	50	1972	43	34	0	229	267
2013	15	16	724	30	33	1795	38	28	0	259	294

Source: New South Wales Bureau of Crime Statistics and Research

Table B1: Full short-run model results (offences - stealing sub-categories 1-6)

	(1) Stealing offences ln(crime)	(2) Break and enter dwelling ln(crime)	(3) Break and enter non-dwelling ln(crime)	(4) Receiving/ handling stolen goods ln(crime)	(5) Motor vehicle theft ln(crime)	(6) Steal from motor vehicle ln(crime)
ln(crime) (lag 1)	0.6350*** (0.0496)	0.5875*** (0.0424)	0.4327*** (0.0562)	0.4629*** (0.1074)	0.5797*** (0.0299)	0.4964*** (0.0963)
ln(crime) (lag 2)	0.1699*** (0.0316)	0.2242*** (0.0346)	0.2416*** (0.0546)		0.1454*** (0.0300)	0.1535*** (0.0444)
ln(crime) (lag 3)	0.0975*** (0.0297)		0.0663 (0.0356)		0.1639*** (0.0263)	0.0905** (0.0365)
ln(proceed_FCAN)	-0.0144 (0.0080)	-0.1135** (0.0570)	-0.0597 (0.0338)	0.0008 (0.0015)	-0.0016** (0.0006)	-0.1472** (0.0639)
ln(narcotics)	0.0024 (0.0015)	0.0015 (0.0019)	0.0013 (0.0015)	0.0025*** (0.0007)	0.0004 (0.0004)	0.0025 (0.0023)
ln(unemployment)	-0.0006 (0.0014)	-0.0000 (0.0012)	0.0009 (0.0009)	0.0003 (0.0004)	0.0010** (0.0005)	-0.0000 (0.0014)
_year1997				0.0003* (0.0002)		
_year1998		0.0006 (0.0004)		0.0001 (0.0002)		
_year1999		-0.0011 (0.0006)	-0.0007** (0.0003)	0.0001 (0.0003)	-0.0005** (0.0002)	-0.0003 (0.0005)
_year2000	0.0003 (0.0005)	-0.0004 (0.0005)	0.0002 (0.0003)	0.0001 (0.0003)	0.0000 (0.0002)	0.0004 (0.0007)
_year2001	-0.0003 (0.0005)	-0.0005 (0.0003)	0.0000 (0.0003)	0.0002 (0.0002)	0.0001 (0.0002)	-0.0002 (0.0005)
_year2002	-0.0027*** (0.0005)	-0.0012*** (0.0003)	-0.0013*** (0.0004)	0.0002 (0.0002)	-0.0007*** (0.0002)	-0.0018*** (0.0007)
_year2003	-0.0035*** (0.0005)	-0.0016*** (0.0003)	-0.0014*** (0.0004)	0.0002 (0.0002)	-0.0008*** (0.0002)	-0.0022*** (0.0007)
_year2004	-0.0047*** (0.0006)	-0.0017*** (0.0003)	-0.0022*** (0.0003)	0.0000 (0.0002)	-0.0006*** (0.0002)	-0.0024*** (0.0006)
_year2005	-0.0043*** (0.0007)	-0.0021*** (0.0004)	-0.0017*** (0.0004)	0.0000 (0.0002)	-0.0006*** (0.0002)	-0.0020*** (0.0006)
_year2006	-0.0032*** (0.0008)	-0.0015*** (0.0004)	-0.0012*** (0.0004)	0.0001 (0.0002)	-0.0002 (0.0002)	-0.0019*** (0.0007)
_year2007	-0.0031*** (0.0008)	-0.0010** (0.0005)	-0.0013*** (0.0004)	0.0000 (0.0003)	-0.0002 (0.0002)	-0.0016** (0.0007)
_year2008	-0.0029*** (0.0008)	-0.0014*** (0.0005)	-0.0015*** (0.0004)	0.0001 (0.0002)	-0.0003 (0.0002)	-0.0019** (0.0007)
_year2009	-0.0036*** (0.0007)	-0.0013*** (0.0005)	-0.0014*** (0.0004)	-0.0001 (0.0002)	-0.0003 (0.0002)	-0.0025*** (0.0007)
_year2010	-0.0024*** (0.0008)	-0.0013** (0.0005)	-0.0017*** (0.0004)	0.0001 (0.0003)	-0.0004* (0.0002)	-0.0019*** (0.0008)

_year2011	-0.0020***	-0.0014***	-0.0014***	0.0000	-0.0001	-0.0017**
	(0.0007)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0008)
_year2012	-0.0024***	-0.0014***	-0.0016***	0.0001	-0.0002	-0.0019***
	(0.0008)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0007)
_year2013	-0.0027***	-0.0020***	-0.0015***	-0.0000	-0.0004	-0.0023***
	(0.0007)	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0007)
Observations	2156	2446	2297	2415	2269	2293
Groups	154	154	154	153	154	154
F-statistics	F(20, 154) = 273.1900	F(21,154)= 163.2300	F(21, 154) = 156.8800	F(21, 153) = 43.7000	F(21, 154) = 239.8900	F(21, 154) = 42.6100
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lag limits (ln(crime) (lag 1))	[1, 3]	[1,2]	[1, 2]	[1, 1]	[1, 1]	[1, 2]
Lag limits (ln(crime) (lag 2))	29	[1,2]	[1, 2]		[1, 1]	[1, 2]
Lag limits (ln(crime) (lag 3))			[1, 2]		[1, 1]	[1, 2]
Lag limits (other)		[2, 6]	[2, 2]	[2, 3]	[1, 2]	[2, 6]
Instrument count		34	22	24	24	34
Arellano-Bond tests						
AR(1) Prob > z =	0.0000	0.0000	0.0000	0.0040	0.0000	0.0380
AR(2) Prob > z =	0.9240	0.5180	0.4360	0.1780	0.6800	0.5900
AR(3) Prob > z =	0.6310	0.9430	0.5430	0.4580	0.8750	0.7790
Hansen test Prob > χ^2 =	0.6170	0.6310	0.5440	0.5950	0.8410	0.5560

Standard errors in parentheses

** $p < 0.05$, *** $p < 0.01$

Table B2: Full short-run model results (offences - stealing sub-categories 7-12)

	(7) Steal from retail store ln(crime)	(8) Steal from dwelling ln(crime)	(9) Steal from person ln(crime)	(10) Stock theft ln(crime)	(11) Fraud ln(crime)	(12) Other theft ln(crime)
ln(crime) (lag 1)	0.4183*** (0.0538)	0.4647*** (0.0320)	0.9128** (0.3767)	0.1663** (0.0769)	0.4019** (0.1590)	0.8538*** (0.0927)
ln(crime) (lag 2)		0.2455*** (0.0338)			0.2127* (0.1155)	
ln(proceed_FCAN)		-0.0028** (0.0013)	-0.1705 (1.0679)	-0.0071 (0.0089)	-0.0010 (0.0007)	-0.1340 (0.2270)
ln(narcotics)	-0.0005*** (0.0001)	0.0003 (0.0003)	-0.0049 (0.0321)	-0.0004* (0.0002)	0.0017** (0.0008)	-0.0013 (0.0032)
ln(unemployment)	0.0006*** (0.0002)	0.0005 (0.0004)	0.0009 (0.0075)	-0.0002 (0.0004)	-0.0009 (0.0010)	0.0040 (0.0064)
_year1997	0.0005** (0.0003)		0.0001 (0.0007)	0.0001 (0.0001)		-0.0001 (0.0006)
_year1998	-0.0001 (0.0001)	0.0003** (0.0001)	0.0013 (0.0078)	0.0001 (0.0001)		0.0020 (0.0032)
_year1999		-0.0001 (0.0001)	0.0046 (0.0273)	0.0001 (0.0001)	-0.0004 (0.0003)	0.0037 (0.0057)
_year2000	0.0001 (0.0001)	-0.0000 (0.0001)	0.0027 (0.0158)	0.0001 (0.0001)	-0.0004 |(0.0003)	0.0039 (0.0057)
_year2001	0.0001 (0.0001)	-0.0001 (0.0001)	0.0006 (0.0022)	0.0002* (0.0001)	-0.0003 (0.0003)	0.0016 (0.0041)
_year2002	0.0002** (0.0001)	-0.0001 (0.0001)	0.0006 (0.0031)	0.0001 (0.0001)	-0.0005 (0.0003)	0.0014 (0.0038)
_year2003	0.0004*** (0.0001)	-0.0001 (0.0001)	0.0005 (0.0031)	0.0002 (0.0001)	-0.0007** (0.0003)	0.0010 (0.0035)
_year2004	0.0003*** (0.0001)	-0.0003** (0.0002)	-0.0001 (0.0020)	0.0001 (0.0002)	-0.0004 (0.0003)	0.0014 (0.0045)
_year2005	-0.0001 (0.0001)	-0.0004** (0.0002)	0.0004 (0.0036)	-0.0001 (0.0001)	-0.0005 (0.0003)	0.0015 (0.0043)
_year2006	0.0000 (0.0001)	-0.0005*** (0.0002)	0.0008 (0.0044)	-0.0001 (0.0002)	-0.0001 (0.0003)	0.0021 (0.0046)
_year2007	0.0000 (0.0001)	-0.0005*** (0.0001)	0.0005 (0.0033)	-0.0001 (0.0002)	-0.0002 (0.0003)	0.0019 (0.0049)
_year2008	0.0001 (0.0001)	-0.0005*** (0.0002)	0.0007 (0.0051)	-0.0001 (0.0002)	0.0002 (0.0003)	0.0012 (0.0038)
_year2009	0.0002 (0.0001)	-0.0003 (0.0002)	0.0010 (0.0069)	-0.0002 (0.0002)	-0.0006* (0.0003)	0.0019 (0.0045)
_year2010	0.0001 (0.0001)	-0.0004***	0.0004	-0.0001	-0.0001	0.0019

		(0.0002)	(0.0035)	(0.0002)	(0.0003)	(0.0044)
_year2011	0.0002 (0.0001)	-0.0004** (0.0002)	0.0003 (0.0030)	0.0001 (0.0002)	-0.0002 (0.0004)	0.0018 (0.0042)
_year2012	0.0001 (0.0001)	-0.0004** (0.0001)	0.0004 (0.0032)	-0.0001 (0.0002)	0.0001 (0.0003)	0.0015 (0.0040)
_year2013	0.0002 (0.0001)	-0.0004** (0.0002)	0.0006 (0.0041)	-0.0002 (0.0002)	0.0003 (0.0004)	0.0017 (0.0044)
Observations	0.0001 (0.0001)	2450	2165	2121	2587	2610
Groups	2470	154	151	150	154	154
F-statistics	152	F(21, 154) = 92.4900	F(21, 151) = 14.0100	F(21, 150) = 4.5000	F(20, 154) = 7.3800	F(21, 154) = 33.7800
Prob > F	F(21, 152) = 14.0200	0.0000	0.0000	0.0000	0.0000	0.0000
Lag limits (ln(crime) (lag 1))	0.0000	[1, 1]	[6, 7]	[1, 1]	[2, 2]	[5, 6]
Lag limits (ln(crime) (lag 2))	[1, 3]	[1, 1]				
Lag limits (ln(crime) (lag 3))					[2, 5]	
Lag limits (other)	[1, 3]	[1, 4]	[6, 6]	[2, 4]	[1, 2]	[2, 3]
Instrument count	29	30	22	27	26	25
Arellano-Bond tests						
AR(1) Prob > z =	0.0000	0.0000	0.8700	0.0000	0.0000	0.2510
AR(2) Prob > z =	0.9700	0.1310	0.8770	0.8590	0.0790	0.4020
AR(3) Prob > z =	0.1000	0.9310	0.7240	0.1520	0.4550	0.8360
Hansen test Prob > χ^2 =	0.2550	0.9570	0.4700	0.4340	0.3890	0.8550

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$