INFRASTRUCTURE VICTORIA

Technical paper

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How do crime rates affect property prices?

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[1] This paper has benefitted from comments from participants at seminars at Infrastructure Victoria and additional comments from Benjamin Mante and James Tucker.

Abstract

In this paper we take the first steps to providing parameters capturing the wider impacts of crime when performing cost benefit analysis of investments in justice infrastructure. Specifically, we provide the first set of estimates of the wider impacts of crime for metropolitan Melbourne and regional Victoria. We estimate the effects of two different types of crime on households applying a hedonic regression model to a three year dataset of house prices and characteristics, distances to local amenities and crime rates. We find while an increase in the per capita rate of crime against persons reduces property prices in regional Victoria, it has no such effect in Melbourne. And we find no significant relationship between crimes against property and property prices in either Melbourne or regional Victoria. This implies that when investing in justice infrastructure to deliver services in regional Victoria that are expected to reduce crime against persons, the impact on the broader community (as captured through effects on property prices) should be taken into account in a cost-benefit analysis.

1. Introduction

The cost-benefit analysis of investments in infrastructure supporting the reduction of crime tends to focus on the direct effects and costs associated with crime – especially with respect to the victim or their immediate associates. And there is an extensive set of parameters that can be easily applied in this context (Mayhew, 2003). But crime may cause people to change their behaviour even if they aren't directly impacted e.g. by undertaking preventative measures. In a way these wider effects of crime have a similar impact to a negative externality. This is harder to measure and typically receives less attention in cost benefit analysis (Infrastructure Victoria, 2016). One technique to estimate local impacts of negative externalities is through their effects on property prices as modelled using a hedonic regression (Palmquist, 2005). There is an extensive international literature applying hedonic regressions to estimate the impact of crime but only a limited Australian literature which focuses on Sydney in the early 2000s (Abelson et al, 2013; Alimova and Lee, 2014). As part of Infrastructure Victoria's research program on improving the measures of the costs and benefits associated with infrastructure, we apply this approach to estimating the wider impacts of crime as a first step to generating parameters for use in cost benefit analysis.

This paper reports the first set of results estimating the wider impacts of crime for metropolitan Melbourne and regional Victoria. We estimate, using data from 2013 to 2016, a hedonic regression for all house and unit prices across Victoria. Specifically, we focus on the separate effects of crimes against persons and crimes against property, controlling for house characteristics and distances to a wide set of amenities. To deal with the endogeneity of crime, we construct instrumental variables using crime rates in neighbouring postcodes. We have two sets of findings.

The first finding is that an increase in the per capita rate of crimes against persons reduces property prices in regional Victoria but not in metropolitan Melbourne. Secondly, the per capita rate of crimes against property has no statistically significant effect on property prices in either regional Victoria or metropolitan Melbourne. This has three sets of implications for cost benefit analysis. First, that when investing in justice infrastructure to deliver services in regional Victoria that are expected to reduce crime, the impact on the broader community should be taken into account in a cost-benefit analysis. Secondly, this paper provides new Victorian-specific evidence of how this methodology can be used to generate estimates for this purpose. Finally, when combined with an estimate of the effects of infrastructure on crime rates, the estimates themselves could be drawn on to contribute to an estimate of e the benefits of a particular justice infrastructure investment for a cost benefit analysis.

In the next section we review the literature on the effects of crime on property prices. This is followed by a discussion of the data and econometric model. We then present and discuss the results of our econometric analysis and conclude.

2. Literature

Previous work on the amenity effects of crime has repeatedly considered the extent to which different types of crime could have different effects on property prices. That different types of crime could have different effects on house prices is a priori plausible. There has been less attention on how the effects of crime could differ, also plausibly, by setting e.g. comparing the effects in urban areas with those in regional areas. We first draw from the previous work, as summarised in Table 1, lessons about the impacts of different types of crime on house prices before considering what can be learned about the impacts in different locations.[2]

The main way crimes have been categorised in previous research is whether they are violent crimes against persons or crimes against property. Violent crime against persons has frequently been found to have a significant substantial negative effect on house prices. Significant negative effects, when several types of crimes are included simultaneously in the hedonic regression, are found for Miami (Ihlanfeldt and Mayock, 2010) and all England and Wales (Braakman, 2017). The two Australian studies, which solely consider violent crime, also find significant negative effects (Abelson et al., 2013; Klimova and Lee, 2014). McIlhatton et al (2016) find no significant effect of violent crime, in Belfast, Northern Island, when considered simultaneously with other types of crime but a significant negative effect when considered in isolation. Ceccato and Wilhelmsson (2011) also find, for Stockholm, violent crime has a significant negative effect when considered in isolation.

The results for property crime are more mixed. Ihlanfeldt and Mayock (2010, Braakman (2017) find no significant effect. McIlhatton et al (2016) find two types of property crime are significantly positively correlated with house prices whether considered simultaneously or in isolation. Gibbons (2004) finds criminal damage has a significant negative effect on house prices in London. For Stockholm, when considering each type of crime in isolation, burglaries are found to have the largest effects on house prices. When Wilhelmsson and Ceccato (2015) consider two years of data for the regional Swedish town of Jönköping they only analyse burglary as it is the only type of crime with substantial

[2] Table One and our review omit several early studies that did not tackle endogeneity. These are reviewed in Ihlanfeldt and Mayock (2010).

numbers. They find a significant negative effect for one year of their sample but not the other.

Both Braakmann (2017) and McIlhatton et al (2016) find the catchall ‘Other crime’ category having significant negative effects on house prices but it is difficult to generalise from these results. Total actual (Ceccato and Wilhelmsson, 2011) and perceived (Buonanno et al, 2013) crime are also found to have significant negative effects on house prices (the latter study being for Barcelona).

None of the papers in Table 1 directly consider how the effects of crime vary in different settings. Also, the papers in Table 1 are not sufficiently similar in how the crime statistics are included to make any simple comparisons. Nearly all of the papers have datasets for very large urban areas with Belfast, Jönköping, and, to some extent, Stockholm being a bit smaller. Although the dataset in Braakman (2017) is for all England and Wales, less than fifteen per cent of observations are for rural residences. The main lesson is that crime can affect property prices in all of the settings considered in the literature.

Two papers analyse the indirect effects of crime on individuals. Cornaglia et al (2014) analyses the effects of property and violent crime rates by Local Government Area on individual mental well-being using the 2002 to 2006 waves of the restricted version of the Household, Income and Labour Dynamics in Australia survey. Dustmann and Fasani (2016) similarly analyse the effect of violent and property crime rates by Local Authority for the United Kingdom. In Australia, it is violent crime that has a significant negative effect on mental well-being whereas in the UK property crime has a significant negative effect.

Before concluding, we note two methodological issues. First, all of the studies recognise the potential endogeneity of crime. Two types of endogeneity problems can arise when considering the relationship between house prices and crime because there are unobservable factors that simultaneously influence crime rates and house prices. We discuss the reasons for this in more detail in section 3.2.1 but the consequence of not addressing this problem is that OLS estimates will be inconsistent. The most popular approach to deal with endogeneity in this literature is to use instrumental variables. The only exceptions are Klimova and Lee (2014) who apply a quasi-experimental approach and Braakmann (2017) who relies on extensive area controls to achieve identification. Second, different choices are made about the standard errors. Several papers assume and model spatial correlations. The remaining studies use robust and clustered standard errors.

Table 1 *Review of Previous Literature*

Paper	Data	Measure of Crime	Results	Comments
Abelson et al (2013)	Twelve months of Median house prices by suburb for Sydney in 2008-09	Violent crime	Semi-elasticity of -5.6 for violent crime.	Spatial model allowing for spatially correlated errors and spatial lags across suburbs. Five regional dummies
Klimova and Lee (2014)	House and unit sales prices for 2003-2011 and simultaneous rental rates from a major internet listing service for Sydney	Murder	Elasticity of -3.9 within a year of the murder, less after then.	Difference-in-difference using distant houses as control group. Found no significant effect if used full sample unless used additional controls for murder areas. Robust clustered std errors.
Ihlanfeldt and Mayock (2010)	130 census tracts within Miami-Dade County from 1999-2007.	Seven types: homicide, aggravated assault, robbery, burglary, motor theft, larceny, vandalism considered simultaneously.	Elasticity of about -0.16 for aggravated assault, for -0.11 for robbery	Instruments for crime using changes in most commercial land uses. Robust standard errors.
Wilhelmsson and Ceccato (2015)	Co-op apartment sales in Jönköping, Sweden, for 2005, 2011.	Residential Burglaries	Semi-elasticity of around -1.6 for burglaries only for 2011. Insignificant in 2005.	Instruments for crime (shares of young men, convenience stores). Spatial error model.
Ceccato and Wilhelmsson (2011)	Co-op apartment sales in Stockholm, Sweden, for 2008.	Total, robbery, vandalism, burglary, theft, violence, considered separately	All significant, with elasticities between -0.0037 and -0.21	Instruments for crime. Also considered neighbouring crimes – usually also negative and significant. Spatial error

Paper	Data	Measure of Crime	Results	Comments
				model.
Braakmann (2017)	England and Wales – all transactions 2011-2013	Anti-social behaviour; violence; other; robbery; vehicle, burglary considered simultaneously.	Semi-elasticity of -0.7 for anti-social behaviour; -1.1 violent crime; -0.3 other crime,	Relies on extensive area dummies for identification. Clustered standard errors.
Buonanno et al (2013)	Barcelona – all transactions by one real estate agency between 2004 to 2006	Use victimisation survey to construct measures of security and crime perception. Considered simultaneously	One std dev increase in security increases house prices by 0.65. One std dev increase in perceived crime reduces house prices by 1.3 per cent.	Second stage regresses neighbourhood fixed effects estimated in first stage on crime rate. Also uses IVs: share of youth and victimisation index 20 years earlier. Robust standard errors.
McIlhatton et al (2016)	Belfast – from multiple real estate agencies from 2012 to 2014	Violence; criminal damage; drugs offences; burglary; theft; other, considered simultaneously and separately	Property crimes have significant positive effects. Other has a significant negative effect. Violence, drugs have negative effects if other types omitted	Spatial correlation model. Also uses IVs – deprivation measure, lagged crime and exogenous variables.
Gibbons (2004)	Sample of 8000 residential properties in London between December 2000 and July 2001	Criminal Damage and Burglary	A 10 per cent increase (from the mean) of Criminal Damage reduces house prices by 1.5 per cent. No impact of Burglary	

3. The Model and the data

3.1 The Model

We employ a hedonic regression model to estimate the effect of crime on property values. Hedonic regression models are a commonly used technique to analyse the determinants of house prices. The premise of the hedonic price function stems from the recognition that properties contain a bundle of attributes that are not individually traded in the market, thereby making it unviable to determine the dollar value of each attribute. The technique therefore relies on the buyer's willingness to pay for a property to measure the marginal contribution of each attribute on prices (OECD, 2013).

The economic theory underlying the hedonic regression is that houses are differentiated products traded in a monopolistically competitive market. Each house is modelled as being a bundle of characteristics. In equilibrium the price for the i^{th} house can be expressed as a function of the characteristics of the house and its neighbourhood:

$$P_i = f(C_i, X_{A,I}, X_{OA,i}; \beta_C, \beta_A, \beta_O) \quad (1)$$

where C_i is the characteristics of house *i*. $X_{A,i}$ and $X_{O,i}$ capture access to parks and other neighbourhood characteristics associated with the location of the house and the betas are the sets of parameters associated with each set of characteristics. The implication of the work of Rosen (1974) is that these parameters are determined by the cost of providing housing, including the land, and the demographics and income of potential buyers.[3] This makes the parameters very much location and time specific.

We apply the hedonic price function to determine the effect of increases in crime rates on property values and disentangle the impact of crime by accounting for all

[3] See Sheppard (1999) as the most recent survey of the field and Kuminoff and Pope (2014) as a recent influential theoretical treatment.

observable property and locational characteristics in the model. There is a wide variety of functional forms that can be used for a hedonic regression equation. We use the common log-log form with price and all continuous characteristics logged. Discrete house characteristics are not logged. The hedonic price function takes the following reduced form:

$$Y_{it} = \alpha + \beta S_{it} + \delta L_{it} + \gamma P_{ik} + \varphi_j C_{ikjt} + \rho Q_{it} + \varepsilon_{it,} \qquad (2)$$

where Y_{it} denotes the log of prices for residential property *i* sold in time *t; S_{it}* denotes a vector of time varying structural attributes for property *i,* such as number of bedrooms, bathrooms and so on; L_{it} denotes a vector of potentially time varying locational attributes such as log of distance from the Central Business District (CBD), distance from parks etc.; P_{ik} is an indicator variable for the postal code property *i* belongs within; C_{ikjt} denotes time varying rate of crime of type j at time *t* for properties located within postcode *k; Q_{it}* denotes quarterly year indicator variables; and ε_{it} is the error term. The time indicators are defined such that the intercept captures the log of house prices in the first quarter of 2013. The postcode and time indicator variables are included, in part, to control for some model simplifications and data limitations as well as (for time) seasonal and economy-wide influences as described in more detail in the appendix. We estimate equation (2) separately for crimes against the person and crimes against the property to obtain estimates of their individual effects on property values as has been done in previous work. But we are aware that treating the two crime variables in isolation may lead to omitted variable bias and therefore follow by modelling equation 3 below which includes both crime variables in the same model.

$$Y_{it} = \alpha + \beta S_{it} + \delta L_{it} + \gamma P_{ik} + \varphi_{person} C_{person,ikt} + \varphi_{property} C_{property,ikt} + \rho Q_{it} + \varepsilon_{it,} \quad (3)$$

It is important to note that, with the postcode and time fixed effects, the coefficients on the crime variables in equations (2) and (3) are capturing the effects on house prices in fluctuations in crime rates around their mean. If the average crime rate in one postcode is higher this will be captured by the postcode fixed effects.

This inspires our second analysis where we determine if it is average house prices, over time, that is affected by average crime rates rather than current house prices being affected by current crime rates.

The empirical strategy we follow is similar to the work of Buonanno et al (2013) in their analysis of house price values and the perception of crime. We employ a 2-stage procedure to conduct the analysis. In the first stage we estimate an hedonic house price model via OLS model with individual house prices as our dependent variable and all house characteristics and distances to amenities as our explanatory variables along with quarter-year and postcode-level fixed effects. This model is consistent with equation (2) except that the crime variables are excluded.

In the second stage we estimate a second hedonic regression, as specified in equation (4):

$$\hat{\gamma}_k = \alpha_0 + \beta_1 I_k + \beta_2 \bar{C}_{Person,k} + \beta_3 \bar{C}_{Property,k} + \varepsilon_k \tag{4}$$

The estimated postcode level fixed effect $\hat{\gamma}_k$ is the dependent variable. In other words the unit of observation shifts from individual houses to an estimated postcode level house price. We also use up to three explanatory variables – the average property crime rates, crime rates against the person and average household income, I_k. Average household income is included to capture any other long run determinants of house prices. This can be justified by a model of housing choice where households with the greatest incomes purchase houses in areas with the greatest amenity. Because the dependent variable is an output of a first stage regression the usual standard error formulae are not applicable so we bootstrap standard errors.

3.2 Data

The dataset used to estimate equations (2) to (4) is constructed by combining three distinct datasets. The primary dataset is three years of house price, house characteristics and local amenity data. Crime rates per capita, by postcode, are added to this dataset by drawing on crime statistics by postcode, as provided by the Victorian Crime Statistics Agency and population by postal area, sourced from the Census of Population and Housing. We discuss these three data sources in turn below.

3.2.1 Housing prices and characteristics data.

Table 2 lists the variables we use in the hedonic regression along with their source and units. The sale price of a house is used as the dependent variable. We obtain data for three years between 2013 and 2016 on all residential property transactions within Victoria from CoreLogic – a housing data provider. The reported sale price, which is originally reported to the Valuer General, is adjusted to include estimated stamp duty.[4]

Matched with the sales price is a set of household characteristics, also provided by CoreLogic and the distance to the different types of amenities obtained, using GIS software from maps as reported in Table 2. The resulting dataset is a repeated cross-section.

However, the dataset is not without its limitations, the key one being that it is only available for four waves. A drawback with using datasets with short timespans in crime work is that there may be little variation in crime rates over the four-year study period, particularly considering these study period occurred well after the Global Financial Crisis and covered a relatively sedate period in Victoria in terms of the wider macroeconomy. A second limitation is the amenities included in the maps at a point in time are assumed to be

[4] The stamp duty adjustment must be estimated because we don't observe the actual stamp duty paid. So we assume the official rates apply to all properties. This overstates the actual duty paid for first home buyers, who receive a discount. The number of first home buyers is relatively small so we are not concerned about this. If they are concentrated in particular suburbs the fixed effects should control for any systematic effect.

Table 2 *Summary of variables and sources*

Category	Variable	Units	Source
Property price	Property price	Thousand dollars	CoreLogic
Property characteristics	Land size	Square metres	CoreLogic
	Bedrooms	Number	CoreLogic
	Bathrooms	Number	CoreLogic
	Garages	Number	CoreLogic
	Car spaces	Number	CoreLogic
	Unit	Dummy variable	CoreLogic
Proximity to parks	Metropolitan parks	Distance to nearest	PLM25
	Community and cultural parks	Distance to nearest	Geomark Polygon and PLM25
	Sport and recreational parks	Distance to nearest	Geomark Polygon and PLM25
	Reserves	Distance to nearest	Geomark Polygon
	National and state parks	Distance to nearest	PLM25
	Other parks	Distance to nearest	PLM25
Proximity to services	Shops	Distance to nearest	Geomark Polygon
	Hospital	Distance to nearest	Geomark Polygon
	Police station	Distance to nearest	Vicmap Features Geomark
	Education facility	Distance to nearest	Geomark Polygon
Proximity to transport	Train station	Distance to nearest	PTV Train Station
	Train line	Distance to nearest	PTV Train Track Centreline
	Tram stop	Distance to nearest	PTV Tram Stop
	Freeway	Distance to nearest	Vicmap Transport – Road Network
	Major road	Distance to nearest	Vicmap Transport – Road Network
	Bike path	Distance to nearest	Vicmap Transport – Bike Paths
Proximity to disamenities	Disamenities	Distance to nearest	Geomark Polygon
Location	Coast	Distance to nearest	Framework – Vicmap Index
	Central business district (CBD)	Distance to	Google Maps
Crime	Rate of crimes against the person	Crimes against the person per 1000 persons	See text
	Rate of crimes against property	Crimes against property per 1000 persons	

present for the whole sample period. Given the sample is only for three years this is less of an issue as there are unlikely to be major changes in the existence or purpose of amenities during this period.

3.2.2 Crime data

The crime data is obtained from the Victorian Crime Statistics Agency (CSA). It is a panel dataset containing the number of offences perpetrated in each year, by postcode between 2005 and 2016 in Victoria.[5] For reporting, these offences are grouped into six categories and further broken down into twenty-one sub-categories.

In this paper, we focus on two categories of crime: crimes committed against persons; and crimes committed against property. We focus particularly on these two offence types for two reasons. Firstly, they are the two largest offences committed in Victoria with property and deception offences accounting for 54.3 percent of total crimes committed in 2016 while crimes against the person accounted for 16.0 percent[6] of total crimes. Secondly, we focus on offences that might impact on buyers' utility and in turn their willingness to pay to avoid high crime areas. Home buyers are arguably more likely to be informed of offences in the area that pose a direct threat to their safety such as violent crimes, property theft or break-ins than say crimes committed clandestinely such as 'breaches of court order' or 'drug manufacturing' offences or randomly such as 'public order' offences.

To better capture the types of crimes against property that are more likely to be easily observable and affect the household's valuation of a property before purchase, we

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[5] As tabulated January 18, 2017. For more details see Crime Statistics Agency (2017).
[6] The two smallest crime categories are drug offences (Category 3) which account for 7.0 percent of total crimes in 2016 and offences labelled 'other offences' (Category 6) which accounted for 0.4 percent of all crimes.

adjust the category so to include the sub-categories Property damage, Burglary/breaking and entering, and omit sub-categories Arson, Theft, Deception and Bribery

3.1.3 Population and merging the three datasets

Because some postcodes are substantially more populous than others, in the econometric analysis we did not want to confound crime effects with scale effects so we include in the model the crime rates per thousand people. To construct annual estimates of population by postcode we begin with data obtained from the Australian Bureau of Statistics Censuses of Population and Housing for 2006 (ABS, 2006) and 2011 (ABS, 2011).[7]

The unavailability of population data in non-Census years means we need to recourse to imputation methods for the intervening years. We use linear interpolation (for years 2007-10) and extrapolation (for year 2005 and years 2012-15) methods to generate population estimates for the ABS Postal Area populations in the non-Census years. We use actual and imputed population data to convert crime counts to crime rate figures per 1,000 persons.

We also deal with extreme values in the crime rates by omitting from the sample properties in postcodes with crime rates lying in the top and bottom 1 percentiles. Despite this, we retain 94 percent of house price observations; of the 307,451 observations in the pre-matched dataset, we retain 287,834 observations post-matching.

3.1.4 Descriptive statistics

Table 3 summarises the key variables in the final matched dataset by urban and regional areas. Variable format and definitions are detailed in Table A.2. in the Appendix. As expected, median property values are substantially higher in urban areas as compared to regional areas, as is the standard deviation on this variable. On the other hand, the rate of

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[7] In 2006 the location is at Census night whereas in 2011 the location is usual residence.

Table 3 *Descriptive statistics by region*

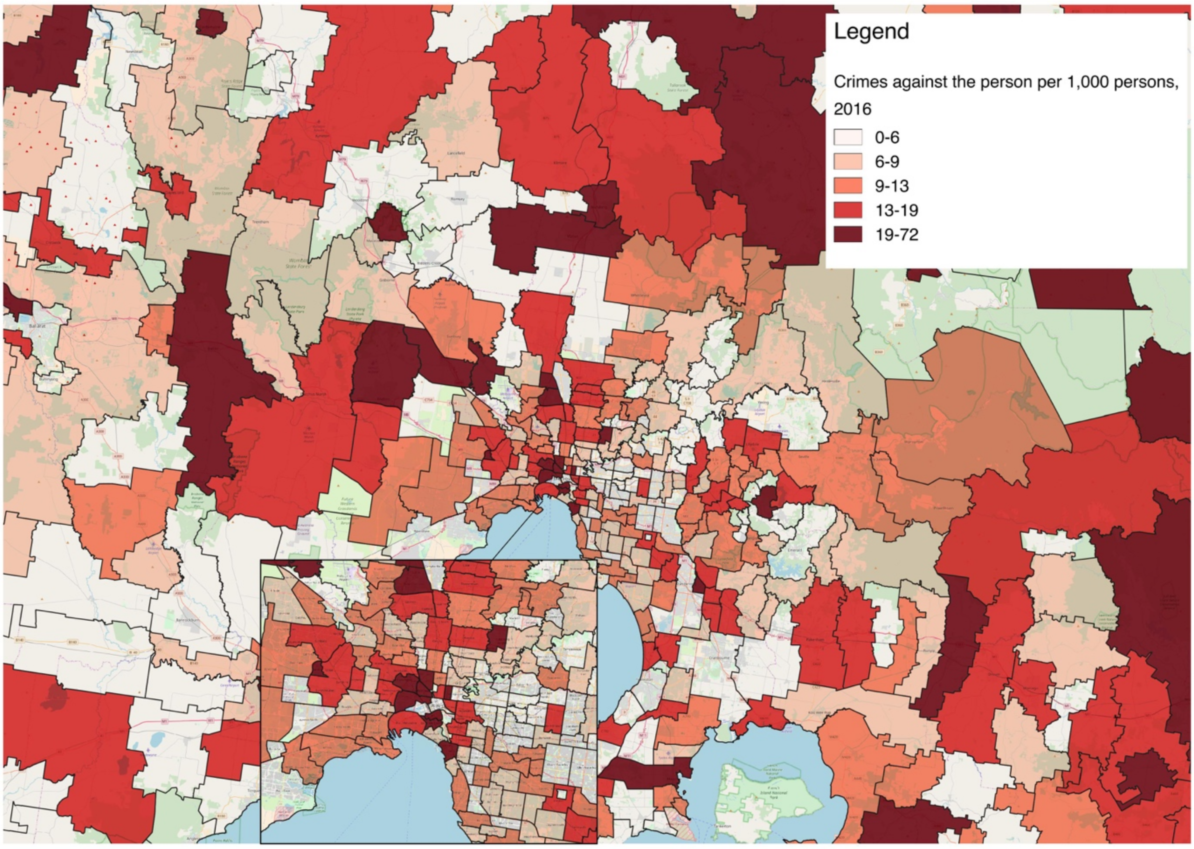
variable	Regional Victoria				Metropolitan Melbourne			
	Median	Standard deviation	Min.	Max.	Median	Standard deviation	Min.	Max.
Property price (thousands)	359	282	51	2321	632	683	51	2458
Rate of crime against the person	13	9.3	0	121	8.8	5.3	0	36
Rate of crime against property	32	17	0	166	29	16	10	133
Land size (square metres)	664	52578	27	1.20E+07	571	25588	25	6580000
No. of bedrooms	3	0.74	1	10	3	0.85	1	10
No. of bathrooms	2	0.59	1	6	2	0.69	1	6
No. of garages	2	1.1	0	10	1	0.99	0	10
No. of car spaces	2	1.2	0	27	2	1.1	0	14
Unit (Mean)	0.11	0.31	0	1	0.23	0.42	0	1
Distance (kilometres) to nearest:								
Metropolitan park	40	103	0.001	503	3.3	2.4	3.8	18
Community and Cultural site	1.4	2.4	0	43	1.2	1.5	0	13
Sports and Recreational site	0.49	0.8	0	34	0.42	0.34	0	8.3
Reserve	0.14	0.44	0	19	0.15	0.15	0	5.6
National and State Park	12	9.6	0	88	14	6.3	0	33
Other park	2.3	3.4	0	24	2.2	1.9	0	10
shops	3.7	25	0	200	0.9	2.4	0	22
hospital	3.5	6.6	3.1	72	2.1	2.1	0	27
police station	2.3	2.8	6.7	46	2.0	1.2	0.023	13
education facility	0.56	1.5	0	45	0.40	0.31	0	7.8
train station	3.3	33	0.05	232	1.4	1.5	0.024	23
train line	2.0	12	0.0012	190	1.1	1.4	.00018	22
tram stop	62	91	0.21	495	4.6	7.5	0.01	40
freeway	6.3	65	0.02	375	2.4	2.7	0.001	34
major road	0.30	0.46	0.0004	9.5	0.23	0.37	.00003	3.9
bike path	3.1	46	0.0003	312	0.61	0.61	0.0006	11
disamenity	2.0	2.0	0	15	1.8	1.0	0	9.6
coastline	22	77	0.0023	340	11	8.3	0.027	55
CBD	68	91	8.8	503	17	9.2	0.11	58

Crimes against the person is higher in regional Victoria than in metropolitan Melbourne and there is greater variability in the distribution in regional areas as indicated by the standard deviation. These regional differences are not present in the crimes against property variable. It is also worth noting the ratio of the standard deviation to the median is highest for crimes against the person in regional Victoria, at 0.72, then crimes against property in metropolitan Melbourne, at 0.60 and then the other cases at around 0.55.

We illustrate the variation in the data by mapping crime rates by postcode for 2016 for crimes against the person (Figure 1) and crimes against property (Figure 2) below. We illustrate crime rates using graduated maps where lighter shades denote relatively low crime areas and darker shades denote high crime postcodes. In 2016, crime rates against the person ranged from zero to 72 per 1,000 persons while crimes against property ranged from zero up to 140 per 1,000 persons in the same year. Quite a few postcodes have zero crime rates and there is considerable variation across postcodes[8]. The maps reveal that population-accounted crimes against the person are fairly evenly distributed across urban and regional areas. This is somewhat surprising given the reputation of inner city areas being magnets for crime. When we turn to crimes against the property however, the high crime status of inner city areas is validated with a higher concentration of property-related crimes in areas surrounding the CBD and relatively lower rates in regional areas. These might be symptomatic of some of the endogeneity issues which we discuss in section 3.2.1. Put directly, there will be more property crime in areas with higher house prices as there is more valuable property to steal.

[8] We requested clarification from CSA for the high values.

Figure 1: *Crime against the person, 2016*



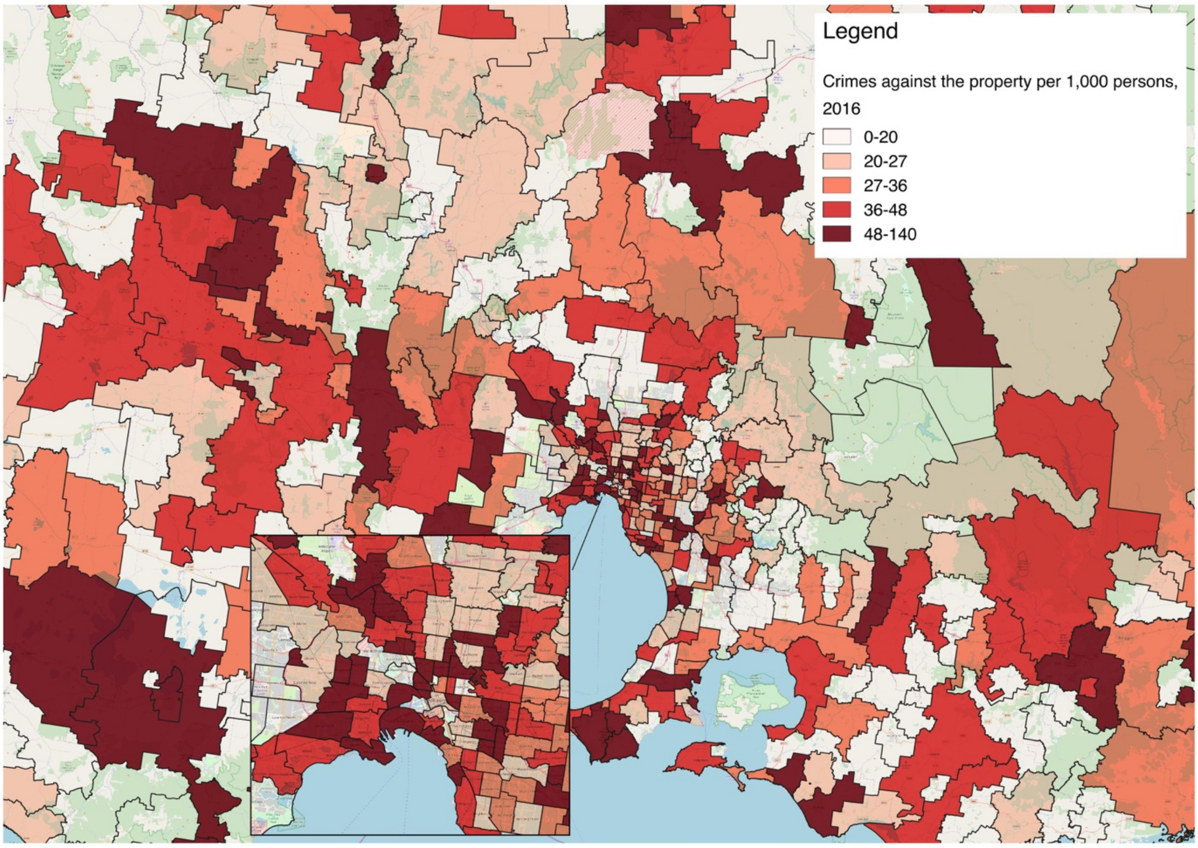
3.2. Identification and model specification

In this section we discuss some potential threats to identification of the effects of crime on house prices, present the results of estimating equations (2) and (3) using OLS and some tests for endogeneity and conclude with a description of the instrumental variables approach we use for the main analysis.

3.2.1 Threats to identification

There are three sets of threats to identification. The first set is suggested from the economic theory in section one. The second set arises from the way the distances to the amenities are constructed. The final set arises from omitted variables that simultaneously determine property prices and crime rates. Each of these threats, unless addressed, could result in our estimates being econometrically inconsistent.

Figure 2 *Crime against the property, 2016*



The economic theory behind the hedonic price function suggests the parameters are determined by the cost of providing housing, including the land, and the demographics and income of potential buyers and so will be location and time specific. The greatest differences in these underlying variables occur between regional Victoria and metropolitan Melbourne. Hence, we divide the Victoria wide sample into these groups.

The potential biases from solely using the distance to the nearest amenity are discussed in the appendix. These are primarily addressed by including time and location fixed effects.

The final threat to identification arises from unobserved features of the location that are correlated with crime. As discussed earlier, this is a concern addressed by all recent papers on the relationship between crime and house prices. There are two potential sources of endogeneity. First, crimes like burglary are likely to be higher in high income/high housing price suburbs as they offer higher payoffs in terms of the market value of stolen goods. For crimes against person, it could be that areas with higher property prices feature amenities that attract crime such as entertainment districts. If not dealt with, this could bias the results towards finding an insignificant or even positive relationship between crime rates and house prices. The second source is that, on average, income and the propensity to commit the types of crimes we are considering are inversely related and neighbourhoods with cheaper houses tend to feature more individuals with lower incomes.[9] This could bias the results towards finding a large effect of crime on house prices. Though it has also been suggested that criminals are more mobile these days which would weaken the effect of the second source.

3.2.2 Ordinary Least Squares estimates

The estimates of the crime parameters in equations (2) and (3), from an Ordinary Least Squares (OLS) model, are presented in columns 2 and 5 of Table 4 (for crimes against the person) and Table 5 (for crimes against property). Separate results are reported for regional Victoria and metropolitan Melbourne.

The results for crimes against the person, as reported in Table 4, are almost identical across equations (2) and (3). For regional Victoria, the coefficient on crimes against the person is in the expected direction (negative) and strongly significant, suggesting that an increase in postcode-level crimes against the person over time has an adverse effect on property values. But for urban areas, the sign on the crime coefficient is perverse (positive) and again strongly significant. This is consistent with there being an endogeneity problem due to high property price areas featuring amenities that attract criminal behaviour.

[9] See Weatherburn (2001) for an extensive discussion of the determinants of criminal behaviour by individuals and those associated with places.

The results for crimes against property, reported in Table 5, are broadly similar to those in Table 4 and do not differ in nature across equations (2) and (3). The signs on the coefficients on crime are negative in regional areas and positive in urban areas. But, unlike for crimes against the person, neither coefficient is statistically significantly different from zero.

We analyse the endogeneity of the crime variables by applying the difference-in-Sargan test[10] for each crime variable in each region, using the instrumental variables specified below. Under the null hypothesis, the suspect crime variable is exogenous. We reject the null hypothesis of exogeneity for crimes against the person in regional Victoria, with a test statistic of 4.412 and a p-value of 0.0357. However, we fail to reject exogeneity for crimes against the person in urban areas or for crimes against the property in both regions. These results reinforce our earlier arguments and findings and so in response we estimate equations (2) and (3) using instrumental variables, as described in more detail in the next subsection.

3.2.3 Instrumental variables estimation

Instrumental variables estimation is used so to yield econometrically consistent estimates of the parameters of interest. This requires supplementing the set of dependent and explanatory variables with a set of instrumental variables. These are variables that will be correlated with crime rates but not correlated with contemporaneous shocks to house prices.

For regional crimes against the person and crime against the property (regional and urban) we use contemporaneous crime rates in the nearest postcode as instruments for crime while urban crimes against the person we use average contemporaneous crime rates

[10] This statistic is produced in Stata's 'endog' option within the ivreg2 command. See Baum et al (2007) and references therein for more details.

for the nearest three postcodes.[11] Intuitively, these instruments are likely to be exogenous because crime rates are likely to be correlated with those in neighbouring postcodes without being correlated with local house price shocks.

To examine the validity of the instruments we perform two tests (Baum et. al, 2007). First, to test for instrument redundancy we perform the Kleibergen-Papp LM test. The null hypothesis of this test is that the instruments are redundant. Secondly, to test if the instruments are weak instruments we use the Kleibergen-Papp F-test.

For all specifications except that of equation (3) for metropolitan Melbourne, the null hypotheses of redundant and weak instruments are clearly rejected. So we proceed with the instruments we have.

Finally, as the threats to identification noted above also apply to the regressions on the effects of average crime rates we also estimate separate regressions for postcodes in regional Victoria and metropolitan Melbourne and use instrumental variables for the crime variables.

4. Results and discussion

4.1 Effects of current crime rates

The first set of results of our study are presented in columns (3) and (6) of Tables 4 and 5. Firstly, in regional Victoria, the rate of crimes against the person statistically significantly reduces house prices. Specifically, an increase in crimes against the person by one person (per thousand) in a postcode is associated with around a one per cent decrease in property values. If we include both crime rates in the regression equation, then the effect is just under one per cent whereas if we only include crimes against the person the effect is

[11] We use QGIS Mapping software to estimate distance measures and to identify nearest postcodes. The nearest neighbour for urban crimes against the person was not supported by the Cragg-Donald Wald F statistic while it was supported when we took the average of the three nearest neighbours.

just over one per cent. To put this into context, for persons living in a house in the top percentile of regional crime rates (where crime against the person is 42 per 1,000), a 10 per cent increase of crime rates to 46.2 per 1,000 would bring about a five percent decrease in property values.

There is no effect of changes in the rates of crimes against the person in metropolitan Melbourne or crimes against property in either region. When crimes against the person is considered in isolation, the direction and size of the effect for crimes against the person in Melbourne is similar to that in regional Victoria but the effect is not even close to being statistically significantly different from zero. When crimes against the person is considered jointly for metropolitan Melbourne, the coefficient remains statistically insignificantly different from zero.

The different effects of crimes against the person for regional and metropolitan areas is probably due, in part, to greater differences in rates of crime across regional Victoria. Regional Victoria reports a larger number of mean and standard deviation in the crime rates against the person in regional areas compared with Melbourne. With greater variation, buyers weighing up two regional locations will be willing to pay more to live a place with less crime. Because there is less variation in crime rates across metropolitan Melbourne, buyers do not respond to difference that are not there. It is likely that Melburnians expect a certain level of exposure to crime irrespective of where they live. Any price premiums are due to other factors.

The models also fail to detect any significant relationship between property related crimes and house prices, irrespective of their regional status. These findings are consistent with much of the literature. One possibility is that there is insufficient variation in the rates of crime against property across locations such that there is no premium for this to living in any particular location. This interpretation is supported by the relationship between the descriptive statistics in the results. There is greater variation in crimes against the person in regional areas than in Melbourne so we find a significant effect in regional Victoria. There is less variation overall in both samples in the rates of crimes against property.[12] Indeed there is a bit more variation in Melbourne but we find no significant effect. The difference in variation is unlikely to be the whole story as the differences in relative variability across the four cases are not that great. So these results also suggestive that home buyers place a different weight on crimes against the person versus those against the property. They indicate that the 'psychic harm' to homebuyers that is brought about by increases in crimes targeted at the person is distinctively more significant than the disutility posed by property-related crimes. One possible explanation for why this may be the case is that some measures of self-protection can be taken to reduce the likelihood of property-related crimes while this is less the case for crimes targeted at individuals. One might set out to prevent the occurrence of burglaries for instance by investing in alarms or cameras but cannot do the same to defend themselves against crimes such as assault or violence. A similar argument can be made with respect to the effects of insurance. This vulnerability might enhance homebuyers' sense of psychic harm in areas where crimes against the person are highest and translate into a lower willingness to pay for houses in high crime suburbs.

We conclude this discussion of the main results by checking that the other components of the model are acting in a plausible manner. First, we consider the signs and significance of the instruments in the first stage of instrumental variable estimation. These results are reported in columns (2) and (4) in Tables 4 and 5. The lower panel of each table includes coefficients from the first stage regression for the associated endogenous variable

[12] This is also consistent with criminals being mobile, travelling to where the returns from crime are greatest.

– crimes against the person in Table 4 and crimes against property in Table 5. Importantly the coefficients on all instruments are statistically significantly different from zero although the sign does vary.

The coefficients on the control variables are reported in Tables A.1. to A.3. In general the signs are as expected. Houses tend to have higher prices if they are on more land, have more bathrooms, bedrooms and parking. In metropolitan Melbourne the prices of units are significantly less than that of houses whereas the reverse holds in regional Victoria. This suggests units may be capturing unobservable features where they tend to be located. Most amenities variables have the expected signs. Property prices tend to be higher near railway stations but lower when they are close to train lines, freeways, major roads and other disamenities. Being near parks tends to have positive effects on house prices in regional areas but more mixed effects in urban areas. This could be for similar reasons as to the different effects of crime across the two regions – there is greater variability in distance to parks in regional Victoria. Being closer to the CBD has a positive effect in metropolitan Melbourne but not in regional Victoria but being near the coast always increases house prices.

Table 4 *Regression estimates for Crimes against the person from OLS, 2SLS First Stage and Second Stage Instrumental Variable Model, by region*

	Regional Victoria			Metropolitan Melbourne		
Rate of crime variables	OLS (1)	First stage IV (2)	Second stage IV (3)	OLS (4)	First stage IV (5)	Second stage IV (6)
Crime rates included singly						
Person	-0.001***		-0.0123**	0.00237***		-0.0131
	(0.000285)		(0.00536)	(0.000533)		(0.0219)
Person in the nearest area		0.047***				
		(0.00331)				
Person in the nearest three areas					-0.0322***	
					(0.00279)	
Observations	118,988	100,923	100,923	168,005	167,717	167,717
R-squared	0.701		0.696	0.391		0.429
Crime rates included jointly						
Person	-0.00099***		-0.00969**	0.00236***		-0.005
	(0.000285)		(0.00444)	(0.000534)		(0.040)
Person in the nearest area		0.0335***				
		(0.00352				
Person in the nearest three areas					-0.034***	
					(0.003)	
Property in the nearest area		0.0228***				
		(0.00112)				
Property in the nearest two areas					0.007***	
					(0.0007)	
Observations	118,988	100923	100,923	168,005	155,084	155,084
R-squared	0.701		0.390	0.756		0.756

Notes: Standard errors in parentheses; * denotes coefficient statistically significant at 10%, two-tailed test; ** denotes coefficient statistically significant at 5%, two-tailed test; *** denotes coefficient statistically significant at 1% level, two-tailed test. Models also include a series of property and area-level explanatory variables that are presented in Tables A.1. and A.3. in the Appendix

Table 5 *Regression estimates for Crimes against the property from OLS, 2SLS First Stage and Second Instrumental Variable Model, by region*

	Regional Victoria			Metropolitan Melbourne		
Rate of crime variables	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
	(1)	(2)	(3)	(4)	(5)	(6)
Crime rates included singly						
Property	-0.000175		-0.00142	0.000135		0.000444
	(0.000154)		(0.00228)	(0.000140)		(0.00425)
Property in the nearest area		0.050***			0.0236***	
		(0.0028)			(0.00235)	
Observations	118,988	100,923	100,923	168,005	157,577	157,577
R-squared	0.701		0.399	0.756		0.436
Crime rates included jointly						
Property	-0.000151		0.00388	0.000124		0.00035
	(0.000154)		(0.00247)	(0.000140)		(0.006)
Person in the nearest area		-0.062***				
		(0.00595)				
Person in the nearest three areas					-0.120***	
					(0.012)	
Property in the nearest area		0.0588***				
		(0.00298)				
Property in the nearest two areas					0.059***	
					(0.003)	
Observations						
R-squared						

Notes: Standard errors in parentheses; * denotes coefficient statistically significant at 10%, two-tailed test; ** denotes coefficient statistically significant at 5%, two-tailed test; *** denotes coefficient statistically significant at 1% level, two-tailed test. Models also include a series of property and area-level explanatory variables that are presented in Table s A.2. and A.3. of the Appendix.

4.2 Effects of average crime rates

The results of regressing the postcode fixed effects on crime and income, as specified in equation (4), are presented in Tables 6 and 7 below for crimes against the person and crimes against property. Considering crimes against the person, when these are included, without also including crimes against property, the effects on house prices are negative in both metropolitan Melbourne and regional Victoria. However, unlike the previous case, the effect is only significant in Melbourne.

When the crimes against the person are included alongside crimes against property however, we fail to detect any significant estimates in either regional or urban areas, which suggests that the effect of crime is not so large as to affect postcode-wide home values. Findings on crimes against property continue to be insignificant, both in the individually and jointly estimated models.

This analysis suggests that average crime rates do not have a distinct statistically significant effect on house prices. Any relationship that exists is captured by the effect of current house prices.

Table 6 *Second Stage IV Fixed Effects estimations for crimes against the person*

Variables	Regional Victoria Second stage IV	Metropolitan Melbourne Second stage IV
	Crime rates included singly	
Rate of crime against the person	-0.0011	-0.0597***
	(0.0301)	(0.021)
Average income	0.000016***	3.85e-06
	(4.67e-06)	(2.78e-06)
Observations	407	176
R-squared	0.355	.
	Crime rates included jointly	
Rate of crime against the person	-0.0108	-0.187
	(0.0277)	(17.9)
Rate of crime against property	-0.000058	0.032
	(0.036)	(1.404)
Average income (by postcode)	0.000014**	-0.000012
	(7.02e-06)	(0.002)
Observations	295	155
R-squared	0.234	.

Notes: Standard errors in parentheses; * denotes coefficient statistically significant at 10%, two-tailed test; ** denotes coefficient statistically significant at 5%, two-tailed test; *** denotes coefficient statistically significant at 1% level, two-tailed test.

Table 7 *Second Stage IV Fixed Effects estimations for crimes against property*

Variables	Regional Victoria Second stage IV	Metropolitan Melbourne Second stage IV
	Crime rates included singly	
Rate of crime against property	0.0023	-0.0065
	(0.11)	(0.0088)
Average income	0.000016	0.000013***
	(0.000024)	(2.84e-06)
Observations	295	155
R-squared	0.3454	0.3550
	Crime rates included jointly	
Rate of crime against the person	-0.0108	-0.187
	(0.0277)	(17.9)
Rate of crime against the property	-0.000058	0.032
	(0.036)	(1.404)
Average income	0.000014**	-0.000012
	(7.02e-06)	(0.002)
Observations	295	155
R-squared	0.234	.

Notes: As for Table 6

5. Conclusion

When performing a cost-benefit analysis of investments in infrastructure to deliver services that may reduce crime, the benefits to potential victims of crime as well as the broader community are worthy of consideration. While there exists estimates of the benefits to the victims of crime there is less evidence on the broader community impacts. In this paper we have attempted to estimate the broader effects through examining the effect of two different types of crime on property prices. A theoretical analysis suggests that the effects should differ across regional Victoria and metropolitan Melbourne so we estimate separate equations for each region.

We find that an increase in the per capita rate of crimes against persons reduces house prices in regional Victoria but not in metropolitan Melbourne. This seems to result from their being greater variation in crime rates across regional Victoria than within Melbourne. So households then distinguish between locations based on crime rates in regional Victoria in a way they don't do so within Melbourne. However, the per capita rate of crimes against property has no statistically significant effect on house prices in either regional Victoria or metropolitan Melbourne. Furthermore, additional analysis suggests these effects result from annual fluctuations in crime rates around their mean rather than long run differences in crime rates driving long run differences in prices.

The primary implication of this work for cost-benefit analysis appears to be that when crime varies substantially that the wider effects of crime need to be considered in a cost-benefit analysis. And this work has demonstrated that it is not only possible to do so for Victoria but these effects are significant in regional Victoria. A final potential contribution of this work is that it provides estimates of the value of these effects that if combined with an estimate of the effects of a piece of justice infrastructure on crime rates, applied now in a cost benefit analysis of justice infrastructure in regional Victoria.

But this research also highlights directions for further research to improve on these estimates before use. Specifically, it would be interesting to explore if greater variation in crime rates over longer time periods could also be found to affect house prices. This however, is a matter for further research with a larger dataset.

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A.1 Appendix

In this appendix we provide additional detail on the data and how it was prepared for estimation.

A.1.1 Housing and amenities data

An important simplification that we use is that it is the nearest amenity of its type that is assumed to affect the house price. So an additional amenity of the same type just a bit further from a house is assumed to have no effect on the house price. However, the extent this differs across postcodes is likely to be fixed over three years and so will be picked up by the postcode indicator variables. A related issue is that aerial rather than travel distances are used. The differences are likely to be idiosyncratic and any systematic differences by postcode will be picked up by the postcode dummies.

Although we have an unusually comprehensive complete set of amenities for inclusion in the regression equation, the limitations of these measures with respect to their heterogeneity, creates several potential identification problems.

The first set arises from unobserved heterogeneity of the amenities. For example, a train station is constrained to have the same effect on house prices whether it is a very busy station from which trains leave every few minutes during peak hours or a station near the end of the line which is often skipped by express services. Similarly, all educational facilities are treated as the same whether they are a primary, secondary or tertiary facility. Another way in which amenities differ may be the extent to which they are accompanied by congestion. Amenities of the same type may or may not have congestion problems depending on whether they are in inner Melbourne, the outer suburbs or regional areas. An individual may value an amenity differently if there is congestion.

The second type of identification problems of this sort arise from using distance to the nearest example of the amenity. This could lead to certain specific types of amenities being over-represented in estimation. To make this more concrete, it is highly likely that for most households the nearest educational facility is a primary school. So the coefficient on educational facility is more likely to be with respect to a primary school rather than a secondary or tertiary institution.

The final set of identification issues arises from the different frequencies of different amenities. In metropolitan areas, most households are likely to be near a primary school but there will be some houses that are close to a train station but many houses that are not. We might, therefore, expect a better chance of being able to separate out the effects of train stations than primary schools.

To deal with these challenges we include postcode and time of sale fixed effects. Because our dataset is comprehensive across locations but relatively short over time, the fixed effects should control for effects that are specific to a geographical unit but constant over time, and those which are vary over time but fixed across locations. Dividing the sample between regional Victoria and metropolitan Melbourne will also assist with these issues.

A.1.2 Crime data

The offence records used to generate the data include those collected by the police as well as from victim reports and family incidents. Traffic infringements, offences for which other agencies, such as the Federal Police, are responsible and offences by Victorians outside of Victoria are excluded. Crime data is available on the following six broad categories of crime (further broken down into 21 sub-categories):

1. Crime against the person

2. Property and deception offences (Arson, Property damage, Burglary/breaking and entering, Theft, Deception, Bribery)
3. Drug offences (Drug dealing and trafficking, Cultivate or manufacture drugs, Drug use and possession)
4. Public order and security offences (weapons and explosives, disorderly and offensive conduct, public nuisance offences, public security offences)
5. Justice Procedures offences (justice procedures, breaches of orders)
6. Other offences (regulatory driving offences, transport regulation offences, other government regulatory offences, miscellaneous offences)

A.1.3 Population data and preparation for estimation

It is important to note that postcodes are not an official ABS geographical classification. However, the ABS has compiled the population data for rough equivalents called ABS Postal Areas which we treat as equivalent (Australian Bureau of Statistics, 2017).

There are a small number of postcodes for which there is crime data but not population data. The main reasons for this are that some postcodes are for post office boxes or have populations so small that it is not possible for them to be reported without breaching confidentiality. This is also a very small number of postcodes for which the failure to match is not clear.

Mismatched postcodes were removed from the final sample along with duplicate sales records[13].

[13] This was a trivial loss with only 107 records of duplicate sales in the Aither sales (i.e. 0.03% of the original dataset).

A.1.4 Complete results

Table A.1. *Other Independent variables used to model effect of Crimes Against the Person*

	Regional Victoria			Metropolitan Melbourne		
Other explanatory variables	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
Land Size	0.149***	0.006	0.151***	0.057***	-0.006	0.059***
	(0.002)	(0.018)	(0.003)	(0.002)	(0.005)	(0.002)
No. of Bedrooms	0.083***	-0.015	0.081***	0.120***	0.003	0.119***
	(0.002)	(0.015)	(0.002)	(0.001)	(0.005)	(0.001)
No. of Bathrooms	0.195***	0.006	0.193***	0.132***	0.0008	0.132***
	(0.002)	(0.018)	(0.002)	(0.001)	(0.006)	(0.001)
No. of Garages	0.037***	-0.00634	0.036***	0.041***	0.012***	0.041***
	(0.001)	(0.0106)	(0.001)	(0.0009)	(0.004)	(0.001)
No. of Car Spaces	0.027***	-0.0105	0.029***	0.022***	-0.006*	0.022***
	(0.010)	(0.0093)	(0.001)	(0.0009)	(0.003)	(0.0009)
Unit	0.013***	0.0018	0.008**	-0.256***	-0.011	-0.255***
	(0.004)	(0.0329)	(0.004)	(0.002)	(0.009)	(0.002)
Log of distance to:						
Community and Cultural site	-0.013***	0.0042	-0.014***	0.005***	0.004	0.005***
	(0.001)	(0.0143)	(0.001)	(0.001)	(0.005)	(0.001)
Sport and Recreational Parks	-0.009***	-0.0009	-0.011***	-0.0002	-0.004	0.00003
	(0.001)	(0.0128)	(0.001)	(0.001)	(0.005)	(0.001)
Reserves	-0.003***	-0.0235**	-0.004***	0.007***	0.003	0.007***
	(0.001)	(0.0103)	(0.001)	(0.0009)	(0.004)	(0.0009)
Metropolitan Parks	N/A	N/A	N/A	0.008***	-0.005	0.00868***
				(0.002)	(0.008)	(0.00163)
National and State Parks	-0.033***	0.039*	-0.030***	N/A	N/A	N/A
	(0.003)	(0.021)	(0.003)			
Other Parks	0.001	-0.009	0.001	-0.0023**	0.003	-0.002*
	(0.001)	(0.016)	(0.002)	(0.001)	(0.007)	(0.001)
Shops	0.0004	-0.018	0.0003	0.009***	0.002	0.010***
	(0.002)	(0.095)	(0.002)	(0.001)	(0.005)	(0.001)
to Hospital	-0.019***	0.033*	-0.019***	-0.008***	0.002	-0.00740***
	(0.002)	(0.019)	(0.002)	(0.002)	(0.006)	(0.00153)
Police Station	-0.033***	0.012	-0.031***	-0.016***	-0.001	-0.016***
	(0.002)	(0.018)	(0.002)	(0.002)	(0.007)	(0.002)
Education Facility	0.008***	0.004	0.007***	0.001	0.010**	0.001
	(0.001)	(0.012)	(0.001)	(0.0009)	(0.004)	(0.0009)
Train Station	-	0.056**	-0.035***	-0.055***	-0.011	-0.055***

	Regional Victoria			Metropolitan Melbourne		
Other explanatory variables	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
	0.035***					
	(0.003)	(0.028)	(0.003)	(0.002)	(0.011)	(0.003)
Train Line	0.027***		0.027***	0.022***	0.0002	0.022***
	(0.002)		(0.002)	(0.002)	(0.007)	(0.002)
Tram Stop	N/A	N/A	N/A	0.002	0.0006	
				(0.002)	(0.007)	
Freeway	0.003**		0.001	0.015***	0.0008	0.016***
	(0.002)		(0.002)	(0.001)	(0.006)	(0.001)
Major Road	0.010***		0.010***	0.018***	-0.005	0.018***
	(0.001)		(0.001)	(0.0008)	(0.004)	(0.0008)
Bike Path	0.013***		0.016***	0.004***	-0.002	0.004***
	(0.001)		(0.001)	(0.0009)	(0.005)	(0.0009)
Disamenity	0.011***		0.011***	0.012***	-0.0007	0.012***
	(0.002)		(0.002)	(0.001)	(0.007)	(0.001)
Coast	-0.140***		-0.146***	-0.133***	0.015	-0.132***
	(0.003)		(0.003)	(0.003)	(0.013)	(0.003)
Central Business District	0.028		0.052	-0.229***	-0.037	-0.246***
	(0.036)		(0.039)	(0.014)	(0.048)	(0.014)
Constant	1.258***			3.398***	0.634**	3.478***
	(0.384)			(0.081)	(0.032)	(0.081)
Observations	118,988	100,923	100,923	168,005	167,717	167,717
R-squared (Centered R-squared for 2nd stage IV)	0.701		0.391	0.756		0.4288
F-statistic			1926.31***			3956.50***

Notes: Standard errors in parentheses; * denotes coefficient statistically significant at 10%, two-tailed test; ** denotes coefficient statistically significant at 5%, two-tailed test; *** denotes coefficient statistically significant at 1% level, two-tailed test. Postcode and year/quarter dummies are also included in the regression models but are not reported in the table due to space considerations. Complete regression estimates are available from the authors upon request.

Table A.2. *Independent variables used to model effect of Crimes Against the Property*

	Regional Victoria			Metropolitan Melbourne		
Other explanatory variables	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
Land Size	0.149***	-0.001	0.150***	0.057***	0.023	0.060***
	(0.002)	(0.038)	(0.003)	(0.002)	(0.024)	(0.002)
No. of Bedrooms	0.083***	-0.015	0.082***	0.120***	-0.016	0.118***
	(0.002)	(0.029)	(0.002)	(0.001)	(0.021)	(0.001)
No. of Bathrooms	0.195***	0.029	0.193***	0.132***	-0.004	0.133***
	(0.002)	(0.037)	(0.002)	(0.001)	(0.023)	(0.001)
No. of Garages	0.037***	0.004	0.036***	0.041***	0.013	0.041***

Other explanatory variables	Regional Victoria			Metropolitan Melbourne		
	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
	(0.001)	(0.020)	(0.001)	(0.0009)	(0.015)	(0.0009)
No. of Car Spaces	0.027***	-0.004	0.029***	0.022***	0.018	0.022***
	(0.001)	(0.019)	(0.001)	(0.0009)	(0.014)	(0.0009)
Unit	0.013***	0.084	0.008**	-0.256***	-0.036	-0.252***
	(0.004)	(0.066)	(0.004)	(0.002)	(0.038)	(0.002)
Log of distance to:						
Community and Cultural site	-0.013***	-0.026	-0.014***	0.005***	-0.001	0.007***
	(0.001)	(0.025)	(0.001)	(0.001)	(0.024)	(0.001)
Sport and Recreational Parks	-0.009***	-0.029	-0.011***	-0.0002	0.022	0.0005
	(0.001)	(0.023)	(0.001)	(0.001)	(0.019)	(0.001)
Reserves	-0.003***	0.004	-0.003***	0.007***	-0.008	0.007***
	(0.001)	(0.021)	(0.001)	(0.0009)	(0.016)	(0.0009)
Metropolitan Parks	N/A	N/A	N/A	0.008***	-0.057*	0.009***
				(0.002)	(0.029)	(0.002)
National and State Parks	-0.033***	0.031	-0.031***	N/A	N/A	N/A
	(0.003)	(0.042)	(0.003)			
Other Parks	0.001	0.011	0.0007	-0.003**	-0.030	-0.0006
	(0.001)	(0.028)	(0.002)	(0.001)	(0.022)	(0.001)
Shops	0.0005	0.025	0.0006	0.009***	0.030	0.010***
	(0.002)	(0.030)	(0.002)	(0.001)	(0.023)	(0.001)
to Hospital	-0.019***	0.032	-0.019***	-0.008***	0.021	-0.006***
	(0.002)	(0.038)	(0.002)	(0.002)	(0.028)	(0.002)
Police Station	-0.033***	0.018	-0.031***	-0.016***	0.014	-0.017***
	(0.002)	(0.038)	(0.002)	(0.002)	(0.030)	(0.002)
Education Facility	0.008***	0.003	0.007***	0.001	0.003	0.001
	(0.001)	(0.023)	(0.001)	(0.0009)	(0.017)	(0.0009)
Train Station	-0.035***	0.008	-0.036***	-0.055***	-0.028	-0.054***
	(0.003)	(0.055)	(0.003)	(0.002)	(0.044)	(0.003)
Train Line	0.027***	-0.045	0.028***	0.022***	0.002	0.021***
	(0.002)	(0.032)	(0.002)	(0.002)	(0.029)	(0.002)
Tram Stop	N/A	N/A	N/A	0.002	-0.009	0.003
				(0.002)	(0.039)	(0.002)
Freeway	0.003**	-0.038	0.002	0.015***	-0.023	0.017***
	(0.002)	(0.033)	(0.002)	(0.001)	(0.027)	(0.001)
Major Road	0.010***	0.047	0.010***	0.018***	-0.012	0.018***
	(0.0009)	(0.019)	(0.001)	(0.0008)	(0.014)	(0.0008)

	Regional Victoria			Metropolitan Melbourne		
Other explanatory variables	OLS	First stage IV	Second stage IV	OLS	First stage IV	Second stage IV
Bike Path	0.013***	-0.025	0.016***	0.004***	0.012	0.004***
	(0.001)	(0.024)	(0.001)	(0.0009)	(0.016)	(0.0009)
Disamenity	0.011***	-0.021	0.011***	0.012***	-0.028	0.012***
	(0.002)	(0.033)	(0.002)	(0.001)	(0.027)	(0.002)
Coast	-0.140***	0.021	-0.146***	-0.133***	0.101***	-0.131***
	(0.003)	(0.042)	(0.003)	(0.003)	(0.032)	(0.003)
Central Business District	0.028	-0.594	0.049	-0.229***	-0.408**	-0.285***
	(0.036)	(0.461)	(0.039)	(0.014)	(0.196)	(0.015)
Constant	1.264***	N/A	N/A	3.393***	N/A	N/A
	(0.384)			(0.082)		
Observations	118,988	100,923	100,923	168,005	157,577	157,577
R-squared (Centered R-squared for 2nd stage IV)	0.701		0.399	0.756		0.436
F-statistic			1943.42***			3791.55***

Notes: As for Table A2.

Table A.3. *Independent variables used to model effect of Crimes Against the Property and Crimes Against the Person*

Other explanatory variables	Regional Victoria				Metropolitan Melbourne			
	OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV	OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV
Land Size	0.149***	0.007	0.001	0.151***	0.057***	-0.007	-0.076***	0.0600***
	(0.002)	(0.018)	(0.038)	(0.003)	(0.002)	(0.006)	(0.023)	(0.002)
No. of Bedrooms	0.083***	-0.016	-0.014	0.081***	0.120***	0.003	0.014	0.120***
	(0.002)	(0.015)	(0.0288)	(0.002)	(0.001)	(0.006)	(0.020)	(0.001)
No. of Bathrooms	0.195***	0.007	0.028	0.193***	0.132***	-0.0005	0.015	0.131***
	(0.002)	(0.018)	(0.037)	(0.002)	(0.001)	(0.006)	(0.023)	(0.001)
No. of Garages	0.037***	-0.005	0.0034	0.036***	0.041***	0.014***	-0.005	0.041***
	(0.001)	(0.011)	(0.020)	(0.001)	(0.0009)	(0.004)	(0.015)	(0.001)
No. of Car Spaces	0.027***	-0.012	-0.0035	0.028***	0.022***	-0.008**	0.019	0.021***
	(0.001)	(0.009)	(0.019)	(0.001)	(0.0009)	(0.003)	(0.014)	(0.001)
Unit	0.013***	0.004	0.084	0.008*	-0.256***	-0.009	-0.115***	-0.254***
	(0.004)	(0.033)	(0.066)	(0.004)	(0.002)	(0.009)	(0.036)	(0.002)
Log of distance to:								
Community and Cultural site	-0.013***	0.004	-0.024	-0.014***	0.005***	0.005	-0.015	0.004***
	(0.001)	(0.014)	(0.025)	(0.001)	(0.001)	(0.005)	(0.022)	(0.001)
Sport and Recreational Parks	-0.009***	0.000	-0.029	-0.011***	-0.0002	-0.006	0.028	0.0006
	(0.001)	(0.013)	(0.023)	(0.001)	(0.001)	(0.005)	(0.020)	(0.001)
Reserves	-0.003***	-0.024**	0.003	-0.004***	0.007***	0.002	-0.006	0.009***
	(0.001)	(0.010)	(0.021)	(0.001)	(0.0009)	(0.004)	(0.016)	(0.001)
Metropolitan Parks	N/A	N/A	N/A		0.008***	-0.006	0.004	0.012***
					(0.002)	(0.008)	(0.028)	(0.002)
National and State	-0.033***	0.039*	0.033	-0.031***	N/A	N/A	N/A	N/A

Other explanatory variables	Regional Victoria OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV	Metropolitan Melbourne OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV
Parks								
	(0.003)	(0.021)	(0.043)	(0.003)				
Other Parks	0.001	-0.010	0.0096	0.0006	-0.003**	0.002	0.015	-0.002
	(0.001)	(0.016)	(0.028)	(0.002)	(0.001)	(0.007)	(0.023)	(0.001)
Shops	0.0004	-0.016	0.025	0.0003	0.009***	0.005	0.016	0.013***
	(0.002)	(0.019)	(0.029)	(0.002)	(0.001)	(0.005)	(0.022)	(0.001)
to Hospital	-0.019***	0.034*	0.031	-0.019***	-0.008***	0.005	0.031	-0.007***
	(0.002)	(0.019)	(0.038)	(0.002)	(0.002)	(0.007)	(0.027)	(0.002)
Police Station	-0.033***	0.012	0.019	-0.031***	-0.016***	-0.003	0.010	-0.017***
	(0.002)	(0.018)	(0.038)	(0.002)	(0.002)	(0.007)	(0.031)	(0.002)
Education Facility	0.008***	0.004	0.002	0.007***	0.001	0.009*	0.025	0.003***
	(0.001)	(0.012)	(0.023)	(0.001)	(0.0009)	(0.005)	(0.017)	(0.001)
Train Station	-0.035***	0.055**	0.009	-0.035***	-0.055***	-0.013	0.005	-0.059***
	(0.003)	(0.028)	(0.055)	(0.003)	(0.002)	(0.012)	(0.043)	(0.003)
Train Line	0.027***	-0.059***	-0.044	0.027***	0.022***	0.003	-0.010	0.024***
	(0.002)	(0.017)	(0.032)	(0.002)	(0.002)	(0.008)	(0.029)	(0.002)
Tram Stop	N/A	N/A	N/A	N/A	0.002	0.002	0.013	0.003
					(0.002)	(0.008)	(0.036)	(0.002)
Freeway	0.003**	-0.014	-0.038	0.002	0.015***	-0.001	-0.016	0.017***
	(0.002)	(0.017)	(0.033)	(0.002)	(0.001)	(0.006)	(0.028)	(0.001)
Major Road	0.010***	0.011	0.047**	0.010***	0.018***	-0.005	-0.024	0.019***
	(0.0009)	(0.010)	(0.019)	(0.001)	(0.0008)	(0.004)	(0.014)	(0.001)
Bike Path	0.013***	-0.017	-0.025	0.016***	0.004***	-0.001	0.022	0.005***
	(0.001)	(0.012)	(0.024)	(0.001)	(0.0009)	(0.005)	(0.016)	(0.001)
Disamenity	0.011***	0.019	-0.021	0.012***	0.012***	0.0008	-0.018	0.010***
	(0.002)	(0.019)	(0.033)	(0.002)	(0.001)	(0.007)	(0.028)	(0.002)

	Regional Victoria				Metropolitan Melbourne			
Other explanatory variables	OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV	OLS	First stage IV (Person)	First stage IV (Property)	Second stage IV
Coast	-0.140***	-0.015	0.021	-0.147***	-0.133***	0.017	0.053*	-0.133***
	(0.003)	(0.018)	(0.042)	(0.003)	(0.003)	(0.013)	(0.028)	(0.003)
Central Business District	0.028	0.148	-0.605	0.054	-0.229***	-0.065	-0.309*	-0.252***
	(0.036)	(0.235)	(0.467)	(0.040)	(0.014)	(0.049)	(0.181)	(0.014)
Constant	1.266***				3.393***			
	(0.384)				(0.082)			
Observations	118,988	100,923	100,923	100,923	168,005	155,084	155,084	155,084
R-squared (Centered R-squared for 2nd stage IV)				0.390				0.436
F-statistic				1845.03***				3623***

Notes: As in Table A2