Abstract

This paper estimates the impact of recorded domestic property crime on property prices in the London area. Crimes in the Criminal Damage category have a significant negative impact on prices. Burglaries have no measurable impact on prices, even after allowing for the potential dependence of burglary rates on unobserved property characteristics. A one-tenth standard deviation decrease in the local density of criminal damage adds 1% to the price of an average Inner London property. One explanation we offer here is that vandalism, graffiti and other forms of criminal damage motivate fear of crime in the community and may be taken as signals or symptoms of community instability and neighbourhood deterioration in general

Keywords: property prices, crime, social disorder, spatial econometrics
JEL Classification: R21, C31

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The Costs of Urban Property Crime

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1. Introduction

Urban crime has a powerful influence on perceptions of area deprivation. Criminal damage to public and private property symbolises urban decay, and fear of burglary and theft promotes insecurity and anxiety. Crime prevention and control policy is top of the political agenda in developed countries, and these problems are particularly acute in the urban environment. Although no place is crime-free, the fear of crime and the direct costs associated with property crime can have particularly severe consequences in urban areas, in discouraging local regeneration and catalysing a downward spiral in neighbourhood status. This 'tipping' process has a prominent role in criminological explanations of community change and crime (Bottoms and Wiles, 1997). Policy makers in Britain apparently share this view, arguing that "neighbourhoods have been stuck in a spiral of decline. Areas with high crime and unemployment rates acquired poor reputations, so people, shops and employers left. As people moved out, high turnover and empty homes created more opportunities for crime, vandalism and drug dealing" (Social Exclusion Unit, 2001, p.7). Certainly, casual observation suggests that persistently high local crime rates deters new residents and motivates those who can to move out to lower-crime rate neighbourhoods. We would expect this demand for low-crime neighbourhoods to be revealed in a property or land price gradient between residences in high and low-crime localities.

The evidence from the US based on hedonic models (Hellman and Naroff, 1979; Thaler, 1978; Lynch and Rasmussen, 2001) suggests that crime rates *do* affect property values, although the effects may be small below high-crime thresholds. Lynch and Rasmussen (2001) find that a 1% increase in violent crime rates reduces prices by 0.05%, but report *positive* associations of property crime rates with prices. This they attribute to higher reporting rates in wealthier neighbourhoods, but higher victimisation rates may provide a better explanation. Properties are heavily discounted in high-crime neighbourhoods. For the UK, however, there is no existing evidence on the relationship between urban crime and property values. We address this here by estimating the effect that crime rates have on property prices in the Inner London area, using spatial property crime data provided by the Metropolitan Police. Following the traditional hedonic literature, we interpret this as measuring households' marginal willingness to pay to avoid crime, or the implicit costs of crime.

One problem with existing studies is that identification relies on inclusion of an ad-hoc set of control variables at the household and neighbourhood levels. No attempt has been made to deal with the potential endogeneity of crime rates in a property value model. In this paper we deal carefully with this issue. We apply a semi-parametric regression approach that is useful for abstracting from unobserved price variation induced by access to local amenities and changes in the unobserved physical characteristics of property over geographical space.

The paper is structured as follows. The next section sets out the empirical framework for our estimates, and goes into some detail on how we think we can identify the impact of crime density on property values. Section 3 discusses our data sources. Section 4 presents the results, and discusses their interpretation. Section 5 concludes.

2. Empirical Model and Methods

Our task is to measure the impact that property-based crimes in the neighbourhood have on the price of residential property. But this highlights a general problem with the use of property value models to infer the implicit price of local characteristics that reflect the behaviour of local residents. Clearly, the behaviour of neighbours will depend on their individual characteristics, and these may well be systematically related to unobserved determinants of property prices. Consequently we may falsely infer a causal relationship between local characteristics and property prices, when in fact it is the unobserved component of property values that drives neighbourhood composition. Consider this example: low local land prices attract low-income residents, and if low-income residents are prone to commit crimes in their own neighbourhood we will find more crime in low land-price neighbourhoods. Unless we can observe land prices, regression estimates of the impact of crime on property prices will be biased towards finding a negative relationship.

On the other hand, estimation of the implicit price of crime presents an additional problem. Burglars will target properties where the expected return in terms of the market value of stolen goods is highest. Since high land-price neighbourhoods will have high proportions of high-income residents, the returns to burglary in high land-price neighbourhoods will be high. We can expect to find high burglary rates in these areas, other things equal. To proceed, we must pay careful attention to the unobserved components of property values that are area specific, and attempt to control for these in our estimation technique.

To understand and tackle the problem, we need to structure what we are doing fairly carefully. We assume the following structure for the joint determination of crimes and property prices:

$$\ln P_i = ßx_i + g'z_i + m(u \mid c_i, h_i) + v_i \tag{1}$$

$$x_i = r\, m(x \mid c_i, h_i) + d'z_i + l\, m(u \mid c_i, h_i) + s\, v_i + e_i \tag{2}$$

Equation (1) says that the log-price of property i is dependent on the incidence of property crimes in the neighbourhood surrounding the property x_i, a vector of exogenous property and location characteristics z_i, plus spatially correlated unobserved components u_i and a random error term v_i. Equation (2) says that crimes in the neighbourhood of a property depend on crimes in the broader geographical area $m(x \mid c_i, h_i)$, on the *observed* property and location characteristics z_i, on the *unobserved* property and location characteristics $m(u \mid c_i, h_i)$, v_i, and on a random error term e_i. The function $m(x \mid c_i, h_i)$ represents a locally weighted average of x, with weights on each observation determined by their distance from the location c_i of observation *i*, with the distance-decay rate determined by a pre-set bandwidth parameter h_i. We can think of this as the expected value of a random variable x in the broader geographical area of observation *i*, and it captures the impact of location and local amenities.

In more detail, the unobservable components in the property price equation (1) are as follows. Firstly, $m(u \mid c_i, h_i)$ represents factors jointly influencing crime and the prices of properties in the broader geographical area – let us call this the *district*. A prime example is the land price, which determines property prices, the supply of criminals and the expected returns to crime in the area. Parameter $l \neq 0$ in equation (2) implies that crimes *in the district* and average district property prices are jointly determined. Secondly, error term v_i represents factors jointly influencing the price of a specific property or properties in its immediate *neighbourhood* and criminal activity at that same location. We might think of large windows or secluded gardens that make a residential area attractive to both burglars and home-buyers, or poorly maintained property that attracts vandals and a low market price. For example, it is known that victimisation rates vary with type of household and so in principle with types of property (Tseloni, Osborn et al., 2002). Hence, recorded crime rates will be endogenous to housing prices unless all housing attributes are observed. So, parameter $s \neq 0$ in equation (2) implies that crimes *at the property or in the immediate neighbourhood* and the property price are jointly determined.

In the crime equation, parameter r measures the dependence of criminal activity in the neighbourhood at a given property location on criminal activity in the surrounding district. This might arise for instance through opportunistic burglaries or vandalism in a street by criminals targeting nearby areas. We allow for spatial correlation in crime rates, since this provides one potential source of identification, as we shall see below.

2.1. Identification of the impact of crime on property prices

As it stands, OLS estimation of the hedonic price function in (1) produces inconsistent estimates, because of the correlation between x_i and the unobserved price components, implied by $s, l \neq 0$. Let us assume for a start that we can proxy the important local determinants of property prices by some parametric function of observable characteristics (distance to the central business district, local amenities and the like), such that $m(u \mid c_i, h_i) = 0$. Parameters estimated in (1) by OLS will still be inconsistent, because we have not dealt with the fact that unobserved property characteristics may determine crime rates in the immediate neighbourhood ($s \neq 0$). But we can obtain consistent estimates by a standard Instrumental Variables estimator, using the spatial lags of crime, $m(x \mid c_i, h_i)$, as instruments, since $E\left[v_i \mid m(x \mid c_i, h_i), z_i\right] = 0$ by assumption. The intuition here is that if reported crime density at a given property location is higher because of unobservable attributes of the properties, then the expected number of crimes in the wider district is a suitable instrument – *but only once we've removed spatial correlation in the unobserved determinants of property prices*[1].

[1] Note that crime density x_i at each location depends on a weighted average of crime densities at other locations $m(x \mid c_i, h_i)$. Hence, x_i itself contributes to $m(x \mid c_i, h_i)$ through other observations' spatial lags, i.e. $x_j = rm(x \mid c_j, h) + \cdots + e_j$. This could invalidate our use of the spatial lags as instruments. However, as the

This is fine if we know what variables to include to get rid of $m(u \mid c_i, h_i)$ and remove the residual spatial autocorrelation. The problem with this approach is that it is data intensive, and we need some prior assumptions about which amenities are important enough to warrant data collection. Moreover, proxying neighbourhood attributes with the characteristics of *owner-occupying residents* will lead to inconsistent estimates, because residents' characteristics are correlated with unobserved determinants of area property prices through sorting and selection processes.

If we do not have this information, the following transformation of (1) is useful. In the fashion of a standard fixed effects estimator, we work in deviations from the local spatial average of the variables (centred on observation *i* at coordinate c_i):

$$\ln P_i - m(\ln P \mid c_i, h_i) = ß\left[x_i - m(x \mid c_i, h_i)\right] + g'\left[z_i - m(z \mid c_i, h_i)\right] + v_i \qquad (3)$$

$$x_i - m(x \mid c_i, h_i) = d'\left[z_i - m(z \mid c_i, h_i)\right] + s\ v_i + e_i - m(e \mid c_i, h_i) \qquad (4)$$

This transformation gets us out of having to specify a full model of price determinants, but means we no longer have a spatial lag instrument for property-specific crimes. One possible source of identification would be a *second* spatial lag of crime rates in equation (2) $m(x \mid c_i, k_i)$, representing spatial impacts at location c_i that operate from distances beyond those implied by $m(x \mid c_i, h_i)$. The difference $m(x \mid c_i, k_i) - m(x \mid c_i, h_i)$ between these spatial lagged values of crime rates then provides a suitable instrument.

Otherwise, an Instrumental Variables procedure requires exclusion restrictions on z_i in (3). A plausible candidate instrument is the number of offences reported on *non-residential* properties in the immediate vicinity. To see this, consider a house in a residential street located near a parade of retail outlets or other commercial premises. The incidence of crimes reported at the commercial premises and the incidence of crimes reported in nearby dwellings will be correlated in that the same criminals may be active in both. But the returns to crime in each type of premises are plausibly uncorrelated[2]. There is little reason to believe that

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number of observations *K* included in the weighted average becomes large, the effect of any individual becomes negligible, so the estimator is consistent if *K* is proportional to the sample size.

[2] Once we have removed common factors like the land price.

victimisation rates in commercial and residential premises will be related, except through *shifts* in the local supply of crimes. In Section 4.4 we consider another instrument, based on the link between alcohol consumption and crime – the distance to the nearest public house or wine bar.

2.2. Estimation

We use all the approaches described above to estimate b. Firstly, we use a fairly traditional specification with property characteristics, location descriptors and physical attributes of the neighbourhood on the right hand side of an OLS regression. Secondly, we use crimes on non-residential properties as instruments for crimes at or near the property.

Next, we estimate the model of equation (3). To do this we need first to estimate $m(x \mid c_i, h_i)$, the sample estimates of the expected values of the independent and dependent variables at each location. These estimates are just locally weighted averages of the neighbouring observations at each data point. Least squares regression using the deviations of the variables from these spatially weighted averages then gives estimates of the linear parameters, as in (3). Details of the procedure for computing the locally weighted averages are presented in Appendix A. Following this, we instrument the deviation of residential crimes from their expected values in the surrounding neighbourhood in (3) with crimes in other dwellings (in similar local deviation form).

As final checks, we use distance to nearest public house or wine bar as an instrument, then spatial lags of crime, and deviations in spatial lags as instruments.

3. Data Sources

3.1. Crime data

Many police forces in the UK record crime at a geographically localised level. However, it is nearly impossible to obtain this data at the present time in a form that is useful for mapping to other area characteristics and to properties. One exception is the Metropolitan Police Force for London, which has made available to us a unique data set recording property-based crime on an annual basis for the period April 1999 to March 2001. The numbers of property-based crimes are recorded across the London area on 100m grid references. We have five types of crime: *Burglary in a Dwelling*, *Burglary in Other Buildings*, *Criminal Damage to a Dwelling*, *Criminal Damage to Other Buildings*, and *Theft from Shops*. Criminal damage includes graffiti and vandalism, but excludes damage committed in the course of a burglary, which would be recorded under burglary (Home Office, 2002). Unfortunately, it seems that the Metropolitan Police is unable to Postcode other offences accurately. Only 68% of offence locations in all offence categories were post-coded in 1999 (Home Office, 2000). Property based crimes are the easiest to Postcode, though no information was available on what proportion of recorded property crimes actually appear in our data set.

These crime statistics are far from perfect for other reasons. It is well known from comparison of victimisation surveys and recorded crime statistics that the latter understate the true incidence of crime – the so-called *dark figure*. Unsurprisingly, the probability to report a crime varies with the severity of the incidence. More troubling is the fact that the propensity to report a crime varies with the characteristics of the victim, so presumably varies over space too. Apparently, individuals with a 'police-neutral' attitude report only 45% of burglaries involving a loss, but without injury or loss of earnings (MacDonald, 2001). More encouragingly, the figure rises to nearly 100% for burglaries involving injury and loss of earnings. No information is available for reporting rates for Criminal Damage. We also know that the police do not record all reported incidents (Home Office, 2000). Some assessment is made about whether a crime really took place, and the incident is recorded or not on that basis.

Ultimately, we will have to live with these data problems. No victimisation or other crime data exists at sufficient density, or at a useful level of geographical dis-aggregation. It is reasonable to assume that the recorded figures in our spatial data set can be treated as an index of the geographical distribution of the most serious incidents of property crime.

3.2. Property price data

Our main data source for property transactions is a sample provided by Ekins Surveyors. Ekins is the trading name of Woolwich Surveying Services Ltd, a wholly-owned but independent subsidiary of Woolwich plc operating in the residential and commercial property sectors. In addition to its work with the Woolwich, Ekins receives survey and valuation instructions from over 100 other lending organisations. The full sample contains 10464 properties in the Inner London Area, covering the E, EC1, N, NW, SE, SW, W, and WC Postcode Areas[3], surveyed between December 2000 and July 2001. We assign these properties to grid references and match in local area data from various sources using the address Postcodes.

Although the sample has a good range of variables characterising the property, many of these have missing or implausible zero values. Keeping only those observations with non-missing data means a massive reduction in sample size. To avoid this, we retain all properties with non-missing values for a basic property style/type indicator that takes on ten mutually exclusive values. Missing data elements in other characteristics are zero encoded, and a new dummy variable generated to indicate missing elements for each characteristic. In a regression setting, this takes out mean differences between missing and non-missing groups in the data[4]. Our final sample with matched grid references amounts to around 8100 properties.

Our second property price data source is the Government land registry, which we use as a comparison sample. This data relates to nearly all post-coded property transactions in England and Wales from January 2000 to December 2001. However, it is only available as spatially aggregated data at *Postcode-Sector* level, by four property types: Detached, Semi-Detached, Terraced, Flat/Maisonette.

3.3. Matching crimes to property locations

Most of the recorded crimes do not match property locations exactly, and it is not the intention here to measure attacks on specific properties. Rather, we are interested in obtaining a measure of the expected density of crime in the neighbourhood of a property – think of a few blocks or streets. For our property level data we calculate the number of crimes of each residential crime type recorded within a 250m radius of the property, and the implied density of crimes per kilometre squared. For non-residential crimes, we double the distance to compensate for the lower density of non-residential properties. When we match to our

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[3] In the UK, postal addresses are coded hierarchically by Postcode Area, Postcode District, Postcode Sector and full Postcode.

[4] We have compared our results with a sample restricted to properties with non-missing observations on number of rooms and property style, and find no important differences.

Postcode-sector level data, we measure crime density within a 1km radius of the Postcode sector centroid.

4. Results and Discussion

4.1. Summarising and visualising the data

Table 1 summarises the key variables in the property price and crime data. The top panel summarises the property valuation sample. The bottom summarises the Postcode-sector based data. The mean crime densities are much lower in the latter, because it covers a much wider geographical area and because, as we illustrate below, crime rates are lower in the suburbs. The focus of our work is on recorded crimes in the categories *Burglary in a Dwelling*, and *Criminal Damage to a Dwelling*.

Table 1:
Summary statistics

	Mean	s.d.	Min / Max	N
Ekins property valuation data				
Property prices, 12/00-07/01 (£000)	235.4	244.8	14 / 4500	8084
Criminal damage in a dwelling (km^{-2})	50.5	30.5	0.63 / 155.8	8084
Burglary in a dwelling (km^{-2})	121.6	79.4	1.2 / 565.3	8084
Eastings	53091	676	51470 / 54840	8084
Northings	18064	664.6	16690 / 19590	8084
Land Registry Postcode sector data				
Property prices, 01/99-12/00 (£)	218.2	246.4	37.5 / 9535	5406
Criminal damage in a dwelling (km^{-2})	37.8	31.9	0 / 191.3	5406
Burglary in a dwelling (km^{-2})	78.8	63.5	0 / 370.2	5406
Eastings	52926	992	50684 / 55200	5406
Northings	17911	864	15937 / 19820	5406

Figure 1 and Figure 2 illustrate the geographical distribution of these crimes for the London area, for the period under study – those crimes recorded from April 1999 to March 2001. The maps are constructed by counting crimes within a 1km radius of points on a 500m grid. The maps indicate burglary hot-spots north of Islington in North London, and around Brixton in the south. Criminal damage is high in these areas too, but the hot-spots look more dispersed. They extend north from Islington up towards Tottenham on the west side of the Lea Valley, east into the East End of London, and on the south side of the River Thames towards Woolwich. Recorded property crime rates are generally low in the Central London area, rise in the inner city areas, and fall away again towards the suburbs. The black polygon illustrates the envelope of our property valuation data set.

Turning now to the property valuation data, Figure 3 shows the distribution of property prices over the London sample area. Comparing the maps for crimes and burglaries, we see that most of the high-density crime areas are in the east, and outside the highest price districts in the west. But this is not the relationship we want to measure. We need to abstract from these broad geographical trends.

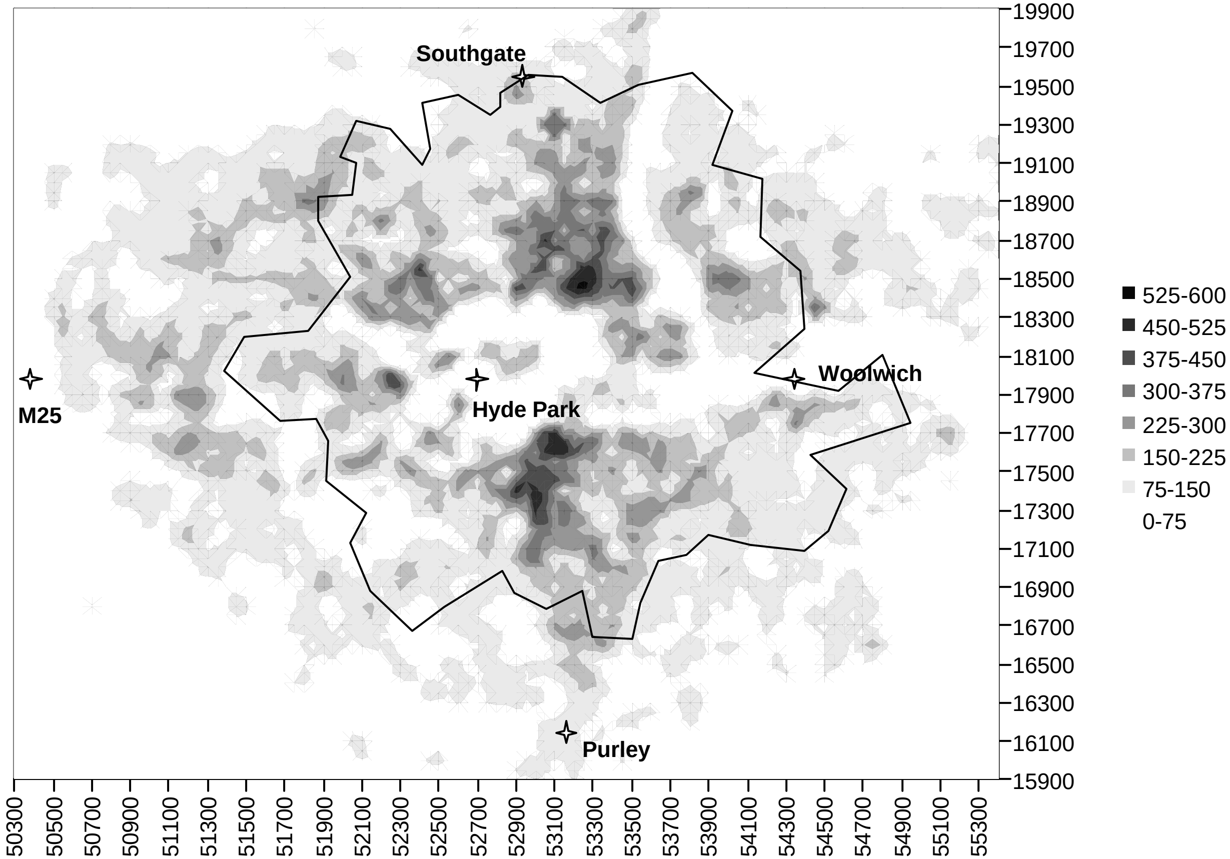

Figure 1: Incidents of Burglary in a Dwelling per km^2, April 1999-Mar 2000 (regression adjusted for household density)

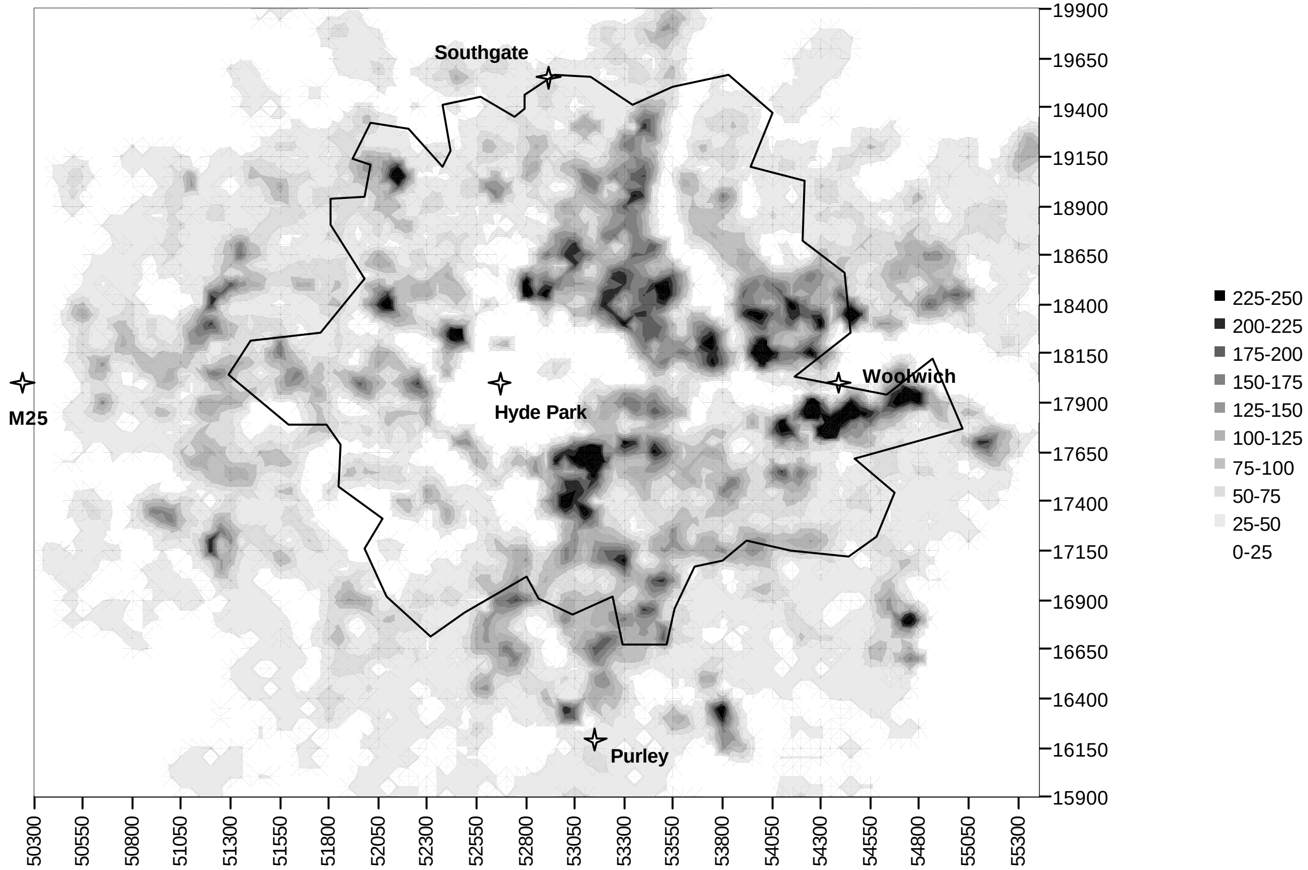

Figure 2: Incidents of Criminal Damage to Dwellings per km^2, April 1999- Mar 2000
(regression adjusted for household density)

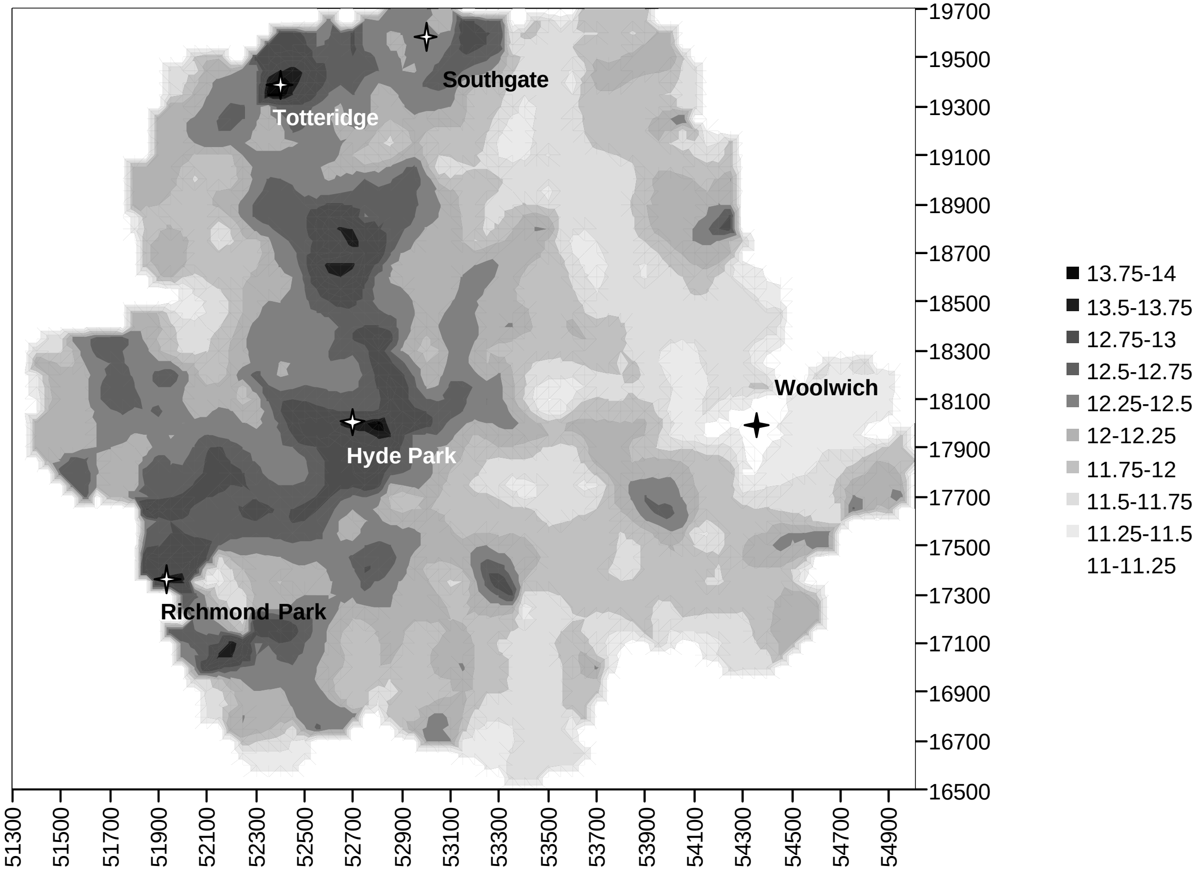

Figure 3: Log Property Prices, First 6 Months of 2001

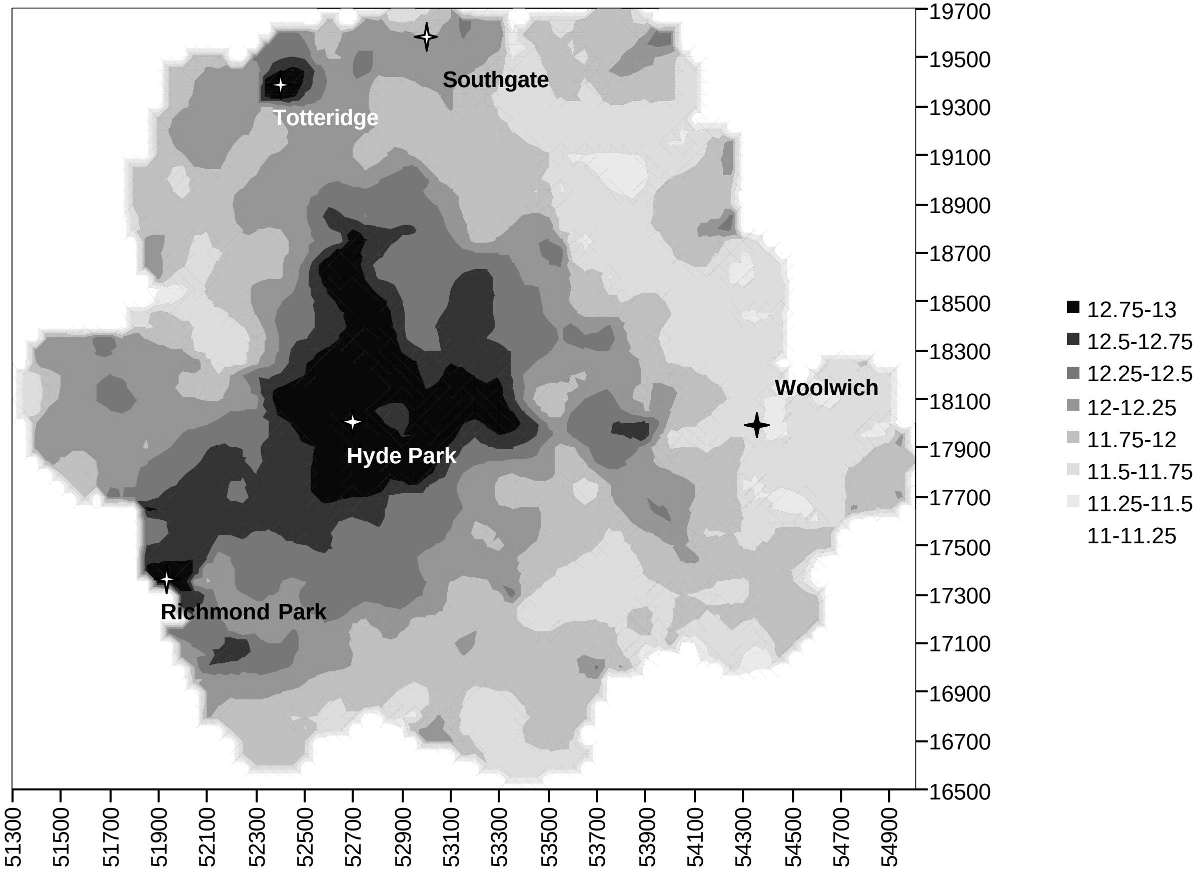

Figure 4: Residual Log-Property Price Surface

Figure 4 presents an estimated contour plot of the *residual* property price surface from our models in the London area, smoothed on to a 500m grid. This is an estimate of the function $m(u \mid c_i, h_i)$ as it appears in (1) (for details of how this is constructed see Appendix A). Our semiparametric method in effect removes this spatial variation before estimating the linear parameters in the hedonic model. It is quite clear that no parametric function can be accurately fitted to this price surface. Any fully parametric property price regression that fails to control adequately for this spatial distribution of unobserved price factors will, in principle, provide inconsistent estimates of the model parameters.

4.2. Regression results using property level data

Let us begin though with standard OLS log-property price regressions. These results are shown in Table 2, Column (1). Explanatory variables are dictated largely by what is available in our property data set. Column (1) includes a quadratic in the distance to Soho, London. This is an approximation to the Central Business District (CBD)[5]. The regression includes various measures of population and household density to adjust for the fact that we measure property crimes on a per-unit-area basis[6]. Crime density could proxy for housing and population density. For presentational reasons we do not report the coefficients on ten property style dummies. All the estimated parameters on the property characteristics and distance to the CBD seem plausible[7].

Focussing now on our crime incidence variables, the first coefficients in Column (1) suggest a highly significant 3.9% decrease in property prices for an additional 5 reported incidents of Criminal Damage per square kilometre per year (10% of the sample mean, or an

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[5] Including alternative or additional measures – to the City of London, Victoria, or Docklands – made little difference to the key results, and introduced collinearity problems.

[6] The alternative approach would be to calculate the impact of crimes per household. This would involve either additional computation of the number of households corresponding to our crime density measure, or division of the crime density by the housing density. Results based on this approach tend to be highly sensitive to the choice of area over which household density is computed, though qualitatively similar to what is presented here. An additional problem occurs, in that we have no sensible denominator for crimes on commercial premises.

[7] The results shown are based on the maximal sample with basic property style indicators and at least some information on other characteristics. We zero-encode data elements in the property characteristics set with missing values and generate an additional missing data dummy for each variable.

expected 1 additional reported incidents per year within a radius of 250m). *But, taking the results at face value, domestic burglaries appear to push up property values*. Following the discussion in 2.1, we assume this implausible (in a causal sense) coefficient reflects the dependence of property crime victimisation on unobserved property, household and neighbourhood characteristics. Higher returns to burglaries in higher-price dwellings, and the higher propensity for better-off households to report crime could bias these estimates[8]. Column (2) introduces more neighbourhood and amenity controls. Immediately, the coefficient on Criminal Damage is halved and the impact of Burglaries vanishes to insignificance. Column (3) instruments crimes on dwellings with the reported incidence of Criminal Damage and Burglaries to other buildings. These IV estimates will be consistent even if victimisation rates depend on the characteristics of dwellings or households. In fact, the IV point estimate is slightly higher than the OLS estimate, but not significantly so using a standard Hausman test of exogeneity ($c_1^2 = 0.583$, *p*-value =0.445).

In any property value model we must worry about the impact of unobserved local amenities. Column (4)-(6) present results for our semi-parametric smooth spatial effects estimator that allows for unobserved spatially correlated effects on property prices. These are just regression estimates obtained after differencing all the variables from their locally weighted averages. Allowing for these spatial effects in Column (4) immediately gives similar results to the more standard property models in Columns (1)-(3), even though we include only the most basic property characteristics. Including a few more neighbourhood characteristics – specifically the neighbourhood proportion in social housing – attenuates the estimated impact of Criminal Damage slightly. Instrumenting with incidents on buildings other than dwellings pushes the coefficients back up. This could be because households in higher-price properties have a higher propensity to report acts of criminal damage. The recorded crime density is endogenous to property prices, and means the non-IV estimates are biased toward finding a positive relationship between incidents and prices. In any case, we not reject the equality of the Criminal Damage coefficients in Columns (5) and (6) (*p*-value=0.452 in Hausman test).

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[8] Lynch and Rasmussen (2001) also find a positive, though insignificant association between property crimes and property prices in a property value regression.

Table 2:
London property prices and property crimes, 2001

	No spatial effects			Smooth spatial effects			
	OLS	OLS	IV[1]	OLS	OLS	IV[2]	Mean
	(1)	(2)	(3)	(4)	(5)	(6)	
Criminal Damage to Dwellings 100s*	-0.768 (-14.10)	-0.422 (-9.15)	-0.500 (-4.45)	-0.416 (-6.76)	-0.310 (-5.50)	-0.388 (-3.26)	0.51
Burglary of Dwellings 100s*	0.044 (4.03)	3.4e-03 (0.71)	3.0e-04 (0.01)	3.6e-04 (0.06)	2.0e-03 (0.45)	0.017 (1.65)	1.22
Total rooms in property	0.215 (25.40)	0.187 (27.67)	0.187 (27.71)	0.202 (29.69)	0.191 (28.80)	0.191 (28.88)	3.94
Total floor area ($100m^2$)	3.11e-04 (2.86)	3.6e-04 (3.73)	3.7e-04 (3.74)	2.8e-04 (2.91)	4.3e-04 (4.29)	4.1e-04 (4.30)	1.49
Number of floors	0.044 (2.86)	0.048 (4.04)	0.047 (3.91)	0.048 (3.74)	0.048 (4.23)	0.048 (4.18)	1.73
Age of property	2.1e-03 (-8.18)	1.5e-03 (7.54)	1.5e-03 (7.66)	1.9e-03 (9.47)	1.6e-03 (8.45)	1.6e-03 (8.30)	77.17
Garage	0.084 (2.83)	0.120 (5.21)	0.117 (5.13)	0.122 (5.40)	0.109 (4.96)	0.110 (4.95)	0.09
Flat density ($1000s/km^2$)	-0.022 (-4.92)	-9.7e-03 (-4.37)	-0.011 (-3.35)	-0.016 (-5.04)	-9.2e-03 (-4.65)	-8.7e-03 (-3.35)	2.48
Household density ($1000s/km^2$)	0.060 (5.52)	0.038 (5.44)	0.038 (5.02)	0.023 (3.26)	0.023 (4.09)	0.023 (4.08)	5.75
Population density ($1000s/ km^2$)	-0.028 (-6.45)	-0.021 (-7.17)	-0.021 (-6.50)	-0.014 (-4.98)	-0.014 (-5.58)	-0.014 (-5.70)	12.77
Distance to Soho (km)	-0.161 (-8.96)	-0.128 (-5.45)	-0.128 (-5.71)	-	-	-	8.90
Distance to Soho squared	3.6e-03 (3.52)	3.1e-03 (2.67)	3.0e-03 (2.64)	-	-	-	91.66
Km to nearest Underground station	-	-0.031 (-3.09)	-0.031 (-3.04)	-	-0.017 (-1.19)	-0.014 (-0.91)	1.59
Km to nearest council office (town centre)	-	-0.028 (-2.86)	-0.031 (-2.91)	-	-0.016 (-1.01)	-0.016 (-1.01)	2.56
Km to nearest green space	-	-3.4e-03 (0.32)	-1.3e-03 (-0.12)	-	-9.0e-03 (-0.63)	-7.1e-03 (-0.51)	2.56
Km to nearest police station	-	-6.6e-03 (0.44)	-0.013 (-0.79)	-	-0.018 (-1.55)	-0.019 (-1.57)	1.08
Mean rooms in neighbourhood	-	0.086 (9.07)	0.083 (8.47)	-	0.066 (8.84)	0.068 (9.19)	4.91
Neighbourhood social housing	-	-0.368 (-11.33)	-0.351 (-11.17)	-	-0.389 (-12.54)	-0.388 (-13.00)	0.28
Local Authority dummies	No	Yes	Yes	No	No	No	
R^2	0.400	0.718	0.717	0.556	0.586	0.585	
Sample size	8084	8064	8064	8084	8064	8064	
P-value test of restrictions	-	-	Not over-identified		-	0.797	

Dependent variable is log property price. Regressions include ten property style dummies, Local Authority area dummies, and missing data dummies. *t*-statistics adjusted for clustering on Census Enumeration Districts. Instruments are: 1. Density of criminal damage and burglary in other dwellings; 2. Density of criminal damage and burglary in other buildings, and theft from shops.
*Crime units are crimes per year per km^2: April 1999 to Mar 2001.

It is worth discussing the effectiveness of our semi-parametric strategy. That it works is clear from the coefficients on the distance from local amenities. Distance from London Underground stations and distance from Council Offices (a measure of intra-urban centres rather than an amenity in its own right) were both significant at around minus 3% per kilometre in Columns 2 and 3 of Table 2. Now they are not. This happens because we are effectively exploiting variation relative to surrounding neighbourhoods. Distances to anything but immediately proximate amenities will not matter. Working with differences from local averages eliminates distance-to-amenity-related variation and reduces the need for this type of control[9].

Adding some more community characteristics into the regression, we find few dramatic changes. Table 3 presents the main crime coefficients, plus the coefficient on number of rooms, for three additional specifications. Including spatially weighted averages of local school performance and unauthorised school absences in the regression makes very little difference. Controls for ethnicity, education levels and unemployment rates have more of an impact, but as we have discussed before, these residential composition variables are likely to be endogenous.

[9] Because the mean distance from an amenity to houses in a radius around a given house j is a consistent estimate of the distance from that amenity to j. If we work with the deviation of distance from local mean distance, then only amenities that benefit households because of their *immediate proximity* will matter in the regression: park and riverside locations perhaps. Taking deviations from the local group mean eliminates the impact of other local factors.

Table 3
Robustness checks

	Criminal Damage	Burglary of Dwellings	Rooms
Baseline specification, full sample	-0.310 (-5.50)	8.8e-03 (0.45)	0.191 (28.80)
Plus performance and absence in nearest primary/secondary schools	-0.294 (-5.03)	8.8e-03 (0.45)	0.191 (28.63)
Plus higher-educated, black and Indian, unemployment rate, average age (1991)	-0.240 (-4.33)	0.013 (0.69)	0.191 (28.57)
Baseline specification, sample restricted to sample with non-missing rooms data	-0.364 (-5.34)	0.016 (0.57)	0.170 (22.31)

Regressions are otherwise as in Table 2, Column (5).

Restricting the sample to observations with non-missing rooms data gives us a lower coefficient on the number of rooms, but increases the measured impact of incidents of criminal damage. The impact of burglary rates remains insignificant. We shall take Column (5) in Table 2 as the best specification. A 5 crimes per year per km^2 increase (+10% at the sample mean) in the expected density of reported Criminal Damage pushes property prices down by 1.6% ($= \exp\{0.31 \times 0.05\} - 1$). This is quite a substantial impact considering that mean number of incidents is 50, with a standard deviation of 30 incidents per year per km^2. Treating criminal damage as an index of visible crime, we can say that a one-tenth standard deviation increase in crime density leads to a 0.94% decrease in property prices. Interpreting the coefficient as an implicit price in a hedonic function gives us a mean implicit price of around £2200 for a one-tenth of a standard deviation reduction in Criminal Damage incidents the Inner London area. We find no impact from domestic burglary rates, despite carefully attention to identification. For interpretation, read Section 4.5.

We have assumed so far that the response of log property prices to the density of crimes is linear. Figure 6 in Appendix C provides and informal check. It plots the deviation of log property prices from their locally weighted averages, against the deviation of Criminal Damage densities from their locally weighted averages. The relationship is predominantly linear.

4.3. Regression results using Postcode-Sector level data

The primary results above are based on a sample of property transactions for the inner London area only. For comparison purposes, we present similar models using geographically aggregated data from the Government Land Registry. This gives near-universal coverage of property transactions. Property prices are aggregated by the Land Registry to *Postcode-sector* level for four property types (Flats, Detached, Semi-Detached and Terraced houses) for confidentiality reasons. We use Postcode-sectors falling within the envelope of the crime data we have for the Metropolitan Police Force in London. This gives us slightly wider geographical coverage than our property level data. The 1991 Census provides us with information on the average number of rooms for different property types and on other Postcode-sector characteristics, analogous to the neighbourhood measures used in Table 2. Table 4 presents these results.

Column (1) is a simple OLS regression. What is clear here is that the Postcode sector average data does a pretty good job of measuring the impact of property crimes on property prices, taking our results of Table 2, Column (4) as the comparison model. Overall though, the coefficients in Columns (1) and (2) mis-measure the implicit prices of a room, and social housing relative to our baseline. In Column (3) we work with deviations from locally weighted averages of the variables. This puts the implicit prices back in line with the baseline model.

Table 4
Postcode Sector Data, 2000-2001

	No spatial effects	Smooth spatial effects
Criminal Damage to Dwellings 100s/km^2	-0.262	-0.244
	(-5.65)	(-3.86)
Burglary of Dwellings 100s/km^2	0.016	-1.5e-04
	(0.59)	(-0.40)
Mean rooms in neighbourhood	0.311	0.198
	(25.59)	(11.79)
Neighbourhood social housing	-0.214	-0.327
	(-4.38)	(-6.18)
Flat density (1000s/km^2)	-5.4e-03	5.4e-03
	(-1.12)	(1.17)
Household density (1000s/km^2)	0.084	0.013
	(6.58)	(0.95)
Population density (1000s/ km^2)	-0.052	-0.021
	(-8.87)	(-3.46)
Distance to Soho	-0.133	-
	(-19.88)	
Distance to Soho squared	3.0e-03	-
	(14.00)	
Local authority dummies	Yes	No
Sample size	5406	5516

Dependent variable is log-property price. Regressions include three property style dummies, one year dummy, plus constant term.
Robust *t*-statistics in parentheses.

Comparison of Column (3) in Table 2, and Column (5) in Table 4, suggests that micro-geographically aggregated data is quite acceptable for the hedonic analysis of neighbourhood and property characteristics, provided that we take the trouble to carefully account for unobserved neighbourhood effects.

4.4. Alternative instruments

In Section 2.1 we suggested using spatial lags of the crime density as instruments for neighbourhood crime density, on the assumption that *averaged* crime rates at some radius[10] from a property or neighbourhood should be unaffected by the characteristics of the property or neighbourhood. Using this strategy, we still fail to find any impact from Burglaries in Dwellings on property prices. This reinforces the impression that burglary rates really have no causal impact. The results are in the top panel of Table 2. Rather than attenuating the impact of Criminal Damage, this strategy gives us *bigger* negative coefficients: –0.664 (–4.64) using data in levels; –0.680 (–4.02) using the data in deviations from locally weighted averages. As we discussed before in Section 4.2, this may be because the higher propensity of occupants of higher-price dwellings to report crime attenuates the non-IV coefficient. But it may also be because average crime density in the wider geographical area suffers from less measurement error and noise than the locally computed crime densities. Instrumenting corrects for errors-in-the-variables-induced attenuation.

Consideration of the possible cultural factors underlying graffiti, vandalism and other forms of criminal damage suggest another plausible instrument. Alcohol consumption is an associated factor in many types of crime, although the lack of official statistics for the UK makes it difficult to quantify the link (Deehan, 1999). A study in one town in England found that 88% of people arrested for acts of criminal damage, over a period of five months, had been drinking in the four hours prior to the incident (Jeffs and Saunders, 1983). Official statistics for local prisons in the United States indicate that 33% inmates convicted for a property crime, and some 56% of inmates convicted for a public order offence, had been drinking prior to the offence. Of those inmates, around three-quarters had a Blood Alcohol Content in excess of 0.10g/dl at the time of the offence (Bureau of Justice Statistics, 1998). Although the link between alcohol consumption and crime is not necessarily directly causal, alcohol is often a contributory factor in violent crimes and acts of public disorder. This may be because alcohol encourages aggression, induces psychotic states, or decreases inhibitions. Or it may be that some certain social environments encourage both excessive drinking and disorderly or criminal activity (Deehan, 1999; Bottoms and Wiles, 1997). In any case, a link

[10] In practice we use the locally weighted averages computed for each observation as in Section 2.2, but excluding any data points within a radius of 1km of the observation.

between the location of crimes and the location of licensed premises, and the time of offences and the end of licensing hours is widely recognised (Bottoms and Wiles, 1997).

Table 5
Alternative instruments for criminal damage

	Criminal Damage
No spatial effects, spatial lags of crime as instruments	-0.664 (-4.64)
Spatial effects, second spatial lags of crime as instruments	-0.680 (-4.02)
No spatial effects, distance to pub as instruments (cubic)[1]	-0.582 (-3.17)
Spatial effects, distance to pub as instruments (cubic)	-0.472 (-1.92)

Regressions are otherwise as in Table 2.
IV regressions using pub distance as instruments include public house density as additional regressor in property-price equation, to allow for amenity effects.
Note: 1. The instruments in this model fail the Sargan test for the validity of the overidentification (p-value=0.027). All others pass the test at a p-value of 0.200 or greater.

With these considerations in mind, we would expect the incidence of property crime in our London data to be higher at locations near licensed premises. Indeed this is true. Regressing the criminal damage density at each property location on a 3rd-order polynomial in distance from the nearest public house or wine bar, we find significant negative impacts ($F(3,138)=6.43$). For the average property, criminal damage density at a property decreases at the rate of 3.5 crimes per km^2 per year as distance to the nearest pub increases[11]. In the lower panel of Table 5 we employ distance to the nearest licensed premises, and its polynomials as instruments for criminal damage in our property price equation. Again, this instrumental-variables strategy *increases* the estimated negative impact of criminal damage on property values, although the results are not far out of line with the IV estimates in Table 2. The use of

[11] Data on pub locations is from the web edition of the Thomson Local Directory, http://www.infospace.com/uk.thomw/. This result is based on a regression in deviations-from-spatial-means form, with additional controls as in Table 2.

distance to nearest licensed premises as an instrument assumes that there is no direct amenity value from living close to a pub. This is questionable, though our instruments pass the appropriate tests once we allow for general, localised spatial effects. We include local pub density as an additional regressor, under the assumption that accessibility to a variety of drinking establishments is likely to be more important to consumers than close proximity to the nearest. This does have a positive impact on prices in the model with spatial effects – an additional 10 pubs or wine bars per km^2 increasing prices by 2.8%.

4.5. Interpretation and discussion

Burglaries do not seem to influence property prices, but Criminal Damage incidents do. This is, at first, quite surprising. True, home-owners can take preventative action against burglars (alarm systems, barriers) but may not be able to prevent damage to property. But we should consider to what extent our estimated impact of Criminal Damage to Dwellings picks up the cost associated with a high incidence of unobserved crimes – violent crime, robbery, vehicle crime for example.

Our data is slightly limited by the lack of information on crime in other categories. Some unobserved crime categories are cause for concern, because the estimates of the economic costs of these types of crime are high. Brand and Price (2000) estimate that average cost associated with an act of violence against the person is £19000 with serious wounding carrying total costs of £130000. For robbery the figure is £9700 per incident. Clearly, we can expect the costs associated with increased risk of attack associated with a high persistent high local incidence of robbery or violent crime to be capitalised in property values. On the other hand, incidents of assault and robbery may be more important in individual choices about where and when to walk the streets. The location of property crimes is more directly related to choice of residential location.

Unfortunately there is not much data available that allows us to infer anything about the relationship between rates of crimes in different offence categories at a localised geographical level in urban areas[12]. We can do this at a much broader geographical level using recorded crime at the Police Force Area level for England and Wales. Police Force Areas correspond to Counties, with a few exceptions. Whether the cross sectional relationship tells us much

[12] Crime data is collected at Local Authority Level, but not for the Criminal Damage category.

about the relationships between types of offences at the neighbourhood level is pretty doubtful. Nevertheless, the relationships between year-to-year changes in crime rates within Police Force Areas will be informative about the links between different types of criminal activity.

Table 6 reports the coefficients obtained by regressing first differences of various log crime rates (crimes per person) within 43 Police Force Areas on the first differences in log crime rates for Burglary and Criminal Damage. Year dummies to take out general trends.

Crimes in nearly all the offence categories are positively correlated with both Criminal Damage and Burglary, with elasticities of between 0.1 and 0.5. Looking at the joint significance of the coefficients, it seems that only in the case of Robbery and Vehicle Crime are these jointly significantly different from zero. There is a relationship too between Sexual Crimes and Criminal Damage. The number of total crimes in other categories (excluding Criminal Damage, Burglary and Fraud) is quite strongly associated with Criminal Damage and Burglary.

Table 6
Association between year on year changes in Police Force Area crime rates, 1997-1999

	Violent	Theft	Robbery	Sexual
Criminal damage	0.237	-0.011	0.417*	0.529*
	(1.46)	(-0.11)	(2.74)	(1.98)
Burglary	0.232	0.781*	0.500*	-0.159
	(1.07)	(4.74)	(2.22)	(-0.54)
F-test *p*-value	0.205	0.000	0.004	0.086
	Vehicle	Other	Total	Excluding vehicles
Criminal damage	0.376*	0.110	0.215*	0.054
	(4.17)	(0.78)	(3.39)	(0.74)
Burglary	0.373*	0.245	0.452*	0.598*
	(2.99)	(1.74)	(6.86)	(4.55)
F-test *p*-value	0.000	0.155	0.000	0.000

Table shows coefficients and standard errors from regression of first differences of various log crime rates for police force areas, on first differences of log criminal damage and burglary rates.

Regressions include year dummies.

Sample size = 172

It seems that similar factors influence criminal activity in the Robbery, Sexual Crimes, Vehicle Crimes and Criminal Damage categories, or that the same criminals are active in these categories. But once we exclude Vehicle Crimes from Total Crime (Table 6, Column (4), bottom panel), the relationship between Total Crime and Criminal Damage disappears.

We also have some geographically disaggregated crime data for the Derbyshire Police Force Area. This police force records crimes at Census Ward level (around 3000 households). This is not a metropolitan area, but contains a mixture of urban and rural territories. Here we find few significant associations between the annual change in the number of recorded incidents Criminal Damage, Burglary and other crime types. Again, Criminal Damage is significantly associated with Vehicle Crimes (thefts from and of vehicles) and Burglary, but with nothing else.

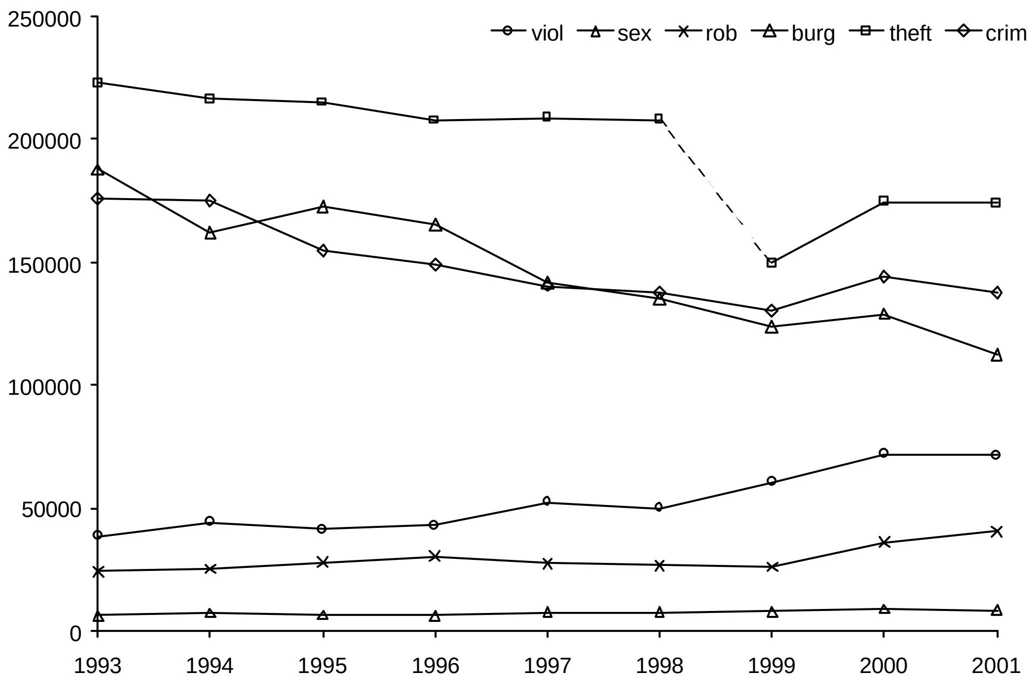

Figure 5: Crime trends in Metropolitan Police Force Area, 1993-2001

Changes in counting rules can make comparison between pre and post 1999 figures misleading. Figures are adjusted for overall effect on offence groups, but the Theft and Handling group cannot be corrected accurately. All vehicle-related crimes (including some criminal damage to vehicles) have been deducted from the Theft and Handling category post January 1998. There were also minor geographical changes to the Metropolitan Police Force boundary in 2000.

The crime trends for the Metropolitan Police Force Area in Figure 5 also suggest little association between criminal activity in the Criminal Damage (crim) category and what we would perceive as serious urban crimes such as Violent Crime (viol), and Robbery (rob). Whilst recorded crimes in the Burglary, Criminal Damage and Theft categories have been on a general trend down in the last decade, Violent Crime and Robbery have been on the increase.

What then are we to make of our results? On the face of it the impact of Criminal Damage on property prices seems high relative to estimates of the direct, physical and emotional costs associated with Criminal Damage itself. Average costs per incident to the household experiencing it are in the order of £510 (Brand and Price, 2000). In comparison, our estimates say that a household is willing to pay something like this to avoid 14 incidents of criminal damage in a square kilometre in their neighbourhood[13]. But a square kilometre in Inner London holds, on average, some 2800 households. Based on the average value of an incident of criminal damage to the household, these 14 incidents should have an expected cost per household in the order of $(14 \div 2800) \times £510 = £2.55$. By the same calculation, if we translate the impact of an increase in the density of crime into an increase in the probability of victimisation, our results suggest that the cost of victimisation is over £100000 for an incident of criminal damage[14]. It is quite clear that if incidents of criminal damage affect property prices, than it is for reasons other than the expected costs of the incidents themselves!

A more likely explanation is that incidents of vandalism and criminal damage impact on property prices because they induce fear of crime. Graffiti, for example, comes out as one of the few neighbourhood factors which is consistently significantly correlated with several measures of fear of crime (Killias and Clerici, 2000). And yet Criminal Damage rates *do not* seem highly correlated with other types of crime, except Burglary – which we have controlled for in our property price regressions – and Vehicle Crime – which again imposes relatively low direct and psychological costs. But Criminal Damage is clearly perceived as a problem by individuals. In the 2000 British Crime Survey, 32% of respondents agreed that vandalism was a 'very/fairly big problem' (Home Office, 2001), although only 10% of these considered it had a negative impact on their quality of life. Nevertheless, in the same study,

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[13] The average cost of an additional 14 crimes in one year in one km^2 = $\exp\{(0.14\times0.310)-1\}\times£235000\times0.05=£522$, assuming the coefficient on crimes in 100s per km^2 per year is 0.31, mean property price = £235000, discount rate = 0.05

[14] We can translate the impact of crimes per km^2 into crimes per household by multiplying by the population density, and evaluating a marginal change in crimes per km^2. The average cost of one crime in one year in one km^2 = £37 (same assumptions as above). So average cost of a crime per household in an average area of $1km^2$ containing 2800 households is $2800\times £37 \approx £104000$.

between 33% and 50% of respondents in owner-occupier neighbourhoods consider that disorder in general has a negative impact on quality of life and one in five respondents in affluent owner-occupier neighbourhoods perceive high levels of disorder.

Perhaps the most plausible interpretation of our results is that incoming residents *perceive* Criminal Damage in the neighbourhood as signalling higher crime in the area, or deteriorating neighbourhood in general. In essence, what we are finding relates to neighbourhood effects of the type described by Wilson and Kelling's *Broken Window Syndrome* (Wilson and Kelling, 1982). According to this hypothesis – popular in the environmental criminology literature and with advocates of neighbourhood cleanup campaigns[15] – unrepaired damage to property in the neighbourhood encourages further vandalism, perceptions of community disorganisation, upward spiralling crime rates and downward spiralling neighbourhood status. If vandalism and graffiti are *seen* as predictors of neighbourhood decline and precursors of escalating crime rates, then it is not surprising that we see them impacting in property prices. Nevertheless, our evidence is that these disorder-related crimes are weakly to moderately associated with more serious crimes, suggesting – like Sampson and Raudenbush (1999) – that the disorder-crime link is not necessarily causal. Physical disorder like graffiti and vandalism may be symptomatic of deeper disruptions in social cohesion and community expectations – what Sampson and Raudenbush call 'collective-efficacy'.

We should also recognise that vandalism, graffiti and other forms of criminal damage are some of the most visible urban crimes. Uncleaned graffiti and unrepaired damage in the environment is hard to conceal from prospective house purchasers. Whilst sellers may have private information about local incidents of other crimes – by personal victimisation, word of mouth or 'Neighbourhood Watch' newsletters – this information is most likely unavailable prospective home-buyers. In London, information on neighbourhood crime rates is not readily available to the general public. This asymmetry in information means that the hedonic price function does not correctly reveal preferences over most types of crime. Hard-to-observe crimes will have a weak impact on property prices.

[15] Almost all citations on the web are on community web-sites in the US, encouraging neighbours to clean up their lots.

5. Conclusion

We have estimated the impact of recorded crimes in the *Criminal Damage to Dwellings* and *Burglary in Dwellings* categories on property prices in the London area, paying careful attention to identification issues. Crimes in the first category – including vandalism, graffiti and arson – have a significant negative impact on prices. Burglaries have *no* measurable impact on prices, even after allowing for the potential dependence of burglary rates on unobserved property characteristics. A one-tenth standard deviation increase in the recorded density of incidents of criminal damage has a capitalised cost of just under 1% of property values, or £2200 on the average Inner London property in our sample 2001. In annual terms, this is around £110 per year per household. Aggregating up to some £340 million per year for all 3.1 million households in the London region. This is a huge impact. By comparison the Safer Communities Initiative offers Crime and Disorder Reduction Partnerships in the London region[16] a total of 3.7 million for 2002/2003 (Home Office, 2001), or around £1.40 per household. Our Instrumental Variables estimates, using a variety of alternative instruments, suggest the figure may be even higher.

It is, on the face of it, surprising that prices respond more to acts of criminal damage than to burglaries given the apparent physical and emotional costs. The explanation we offer here is that vandalism and graffiti are important factors motivating fear of crime in the community, even though the evidence here suggests that these types of crimes are not strongly correlated with incidents of a more serious nature. More generally, graffiti and vandalism may be taken as signals or symptoms of community instability, disorder, lack of social cohesion and neighbourhood deterioration in general.

[16] The 1998 Crime and Disorder Act established partnerships between the police, local authorities, probation service, health authorities, the voluntary sector, and local residents and businesses.

Appendix A: Computing Locally Weighted Averages

This Appendix describes how we compute the locally weighted averages of each variable x and so estimate $m(x \mid c_i, h_i)$. We define:

$$\hat{m}(x \mid c_i, h_i) = \left\{ \sum_{j \neq i} x_j f\left[d_{ij} h^{-1}\right] \right\} \cdot \left\{ \sum_{j \neq i} f\left[d_{ij} h^{-1}\right] \right\}^{-1} \tag{5}$$

$$\begin{aligned} d_{ij}^2 &= (c_i - c_j)'(c_i - c_j) \text{ if } d_{ij} < k \\ &= \infty \text{ otherwise} \end{aligned} \tag{6}$$

$$h_i = s.d.(d_{ij}) \text{ if } d_{ij} < k \tag{7}$$

where $f(\cdot)$ is the standard normal density function. This means we are using a Gaussian kernel or distance decay function to weight neighbouring observations. Parameter k sets the maximum distance to the neighbouring observations that will used to compute these local weighted averages. Our estimator of $m(x \mid c_i, h_i)$ is thus a kernel-weighted nearest neighbour smoother. This is a variation on the Smooth Spatial Effects Estimator of Gibbons and Machin (2001).

Note that the choice of k determines the degree of smoothing. This defines how wide the neighbourhood is over which we compute the locally weighted averages. A higher value of k implies generates a longer spatial lag. The choice of k is somewhat arbitrary, but was found to make little difference in practice over a moderate range. Our baseline choice of k is such that the spatially weighted mean explains around one third of the variation in property prices, as measured by the R^2 in a regression of $\ln P_i$ on $m(\ln P_i \mid c_i, h_i)$.

Appendix B: Constructing the Land Price Surface

Figure 4 illustrates an estimated residual land price surface for the Inner London area. This is an estimate of $m(u \mid c_g, h)$, the expected value of the residuals from the property price equation at map grid points c_g, with a fixed smoothing parameter h. To obtain this map, we first estimate the model in equation (3) to obtain estimates of the linear parameters b, g. Note now that

$$m(u \mid c_g, h) = E[\ln P_i - b'x_i - g'z_i \mid c_g] \tag{8}$$

So we then compute the residuals $\ln P_i - b'x_i - g'z_i$. Next we calculate the locally weighted averages of these residuals within 2.5km of each map grid point, using a Gaussian distance decay function (or kernel).

Appendix C: Linearity of the Crime-Price Function

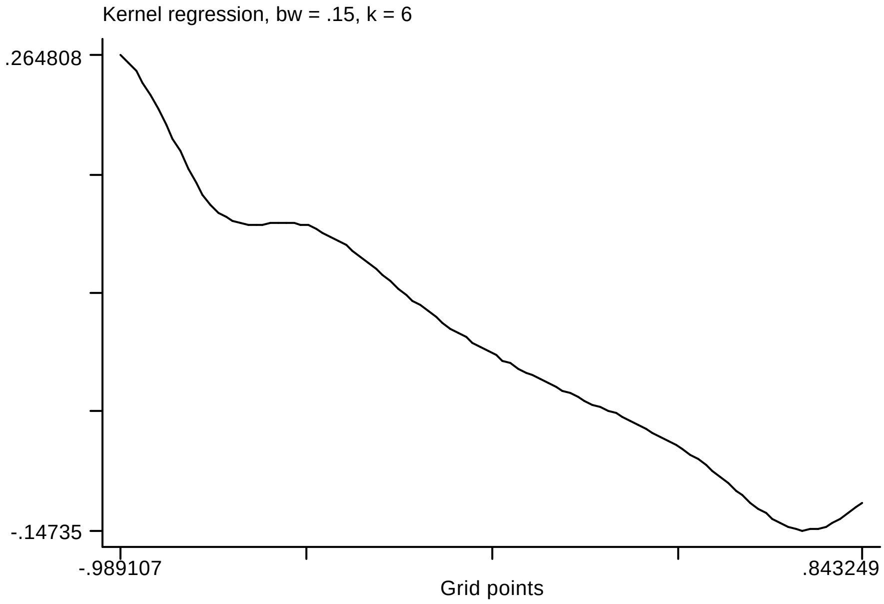

Figure 6: Association between local deviations in Criminal Damage density and local deviations in log property prices

Figure shows kernal regression of log prices (vertical axis) on incidents of Criminal Damage to Dwellings in 100s per km^2 (horizontal axis). Variables are in the form of deviations fom local means. Kernel is Epanechnikov, bandwidth 0.15

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