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THE COSTS OF URBAN PROPERTY CRIME*

Steve Gibbons

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. A one-tenth standard deviation decrease in the local density of criminal damage adds 1% to the price of an average Inner London property. Burglaries have no measurable impact on prices, even after allowing for the potential dependence of burglary rates on unobserved property characteristics. 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.

1. Crime in Cities and the Demand for Low-crime Spaces

Crime in urban areas has effects over and above the direct costs to victims, the costs of deterrence and the costs of law enforcement. The 'fear of crime', whilst not a uniquely urban phenomenon, seems closely related to densely populated and built environments (Bannister and Fyfe, 2001). Urban crime has, in addition, a powerful influence on perceptions of area deprivation. Visible forms of drug use, 'anti-social' behaviour and criminal damage to public and private property have come to symbolise urban decay and social problems. Fear of robbery, burglary and theft promotes insecurity and anxiety. For these reasons, crime prevention and control policy is top of the political agenda in developed countries, particularly in cities, where the problems are acute.

Although no place is crime-free, there is a clear link between city size and crime (Glaeser and Sacerdote, 1999). Even within cities, crime is spatially concentrated. In the borough of Lambeth in London, for instance, there were 37.2 burglaries per 1,000 households in the year 2000. At the same time, in the neighbouring borough of Merton, the figure was only 13.2 (Home Office, 2001*b*). The roots of these wide geographical differences are not fully understood. Some have proposed contextual neighbourhood effects rooted in 'social disorganisation' (Shaw and Mackay, 1942), lack of 'social cohesion' (Bowers and Hirschfield, 1997), or lack of 'collective efficacy' (Sampson and Raudenbush, 1999). Others suggest that higher average local engagement in crime encourages further criminal activity, possibly through social interactions (Glaeser *et al.*, 1996; Case and Katz, 1991), or because of lower probabilities of detection (Freeman *et al.*, 1996; Zenou, 2003). Other ideas are that distance to jobs matters (Verdier and Zenou, 2002), that transport facilities and other local amenities act as crime magnets (Bowes and Ihlanfeldt,

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2001), or that relatively widely dispersed criminals forage over short distances (Costello and Wiles, 2001; Johnson and Bowers, 2004).

Whatever the cause, the spatial concentration of crime can have dynamic effects driven by household location decisions. Fear of crime and the direct costs associated with property crime may discourage home-buyers, inhibit local regeneration and catalyse 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 high crime rates deter new residents and motivate 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, suggests that crime rates *do* affect property values. In early studies, Thaler (1978) claims that a one standard deviation increase in property crime rates decreased prices by 3% in Rochester, New York, whilst Hellman and Naroff (1979) report an elasticity of −0.63 for total crimes in Boston. More recently, Lynch and Rasmussen (2001) find an elasticity of −0.05 for violent crimes in Jacksonville, Florida, 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 another explanation. They find that properties are heavily discounted in the highest-crime neighbourhoods. Bowes and Ihlanfeldt (2001) report that an additional crime per acre per year in census tracts in Atlanta decreases house prices by around 3%, allowing for simultaneous effects from transport access. 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

The task at hand is to measure the effect that property-based crimes in a neighbourhood have on the price of residential property located there. 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:

$$\ln P_i = \beta x_i + \boldsymbol{\gamma}'\mathbf{z}_i + m(u|c_i, h_i) + v_i \tag{1}$$

$$x_i = \rho m(x|c_i, h_i) + \boldsymbol{\delta}'\mathbf{z}_i + \lambda m(u|c_i, h_i) + \sigma v_i + \varepsilon_i. \tag{2}$$

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 $\mathbf{z}_i$, 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 $m(x|c_i, h_i)$, on the *observed* property and location characteristics $\mathbf{z}_i$, on the *unobserved* property and location characteristics $m(u|c_i, h_i)$, v_i, and on a random error term ε_i. The function $m(\xi|c_i, h_i)$ represents a locally weighted average of ξ, 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 ξ 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, $m(u|c_i, h_i)$ 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 $\lambda \neq 0$ in (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 *et al.*, 2002). Hence, recorded crime rates will be endogenous to housing prices unless all housing attributes are observed. So, parameter $\sigma \neq 0$ in (2) implies that crimes *at the property or in the immediate neighbourhood* and the property price are jointly determined.

In the crime equation, parameter ρ 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 $\sigma, \lambda \neq 0$. 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 $m(u|c_i, h_i) = 0$. 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 ($\sigma \neq 0$). But we can obtain consistent estimates by a standard Instrumental Variables estimator, using the spatial lags of crime, $m(x|c_i, h_i)$, as instruments, since $\mathrm{E}[v_i|m(x|c_i, h_i), z_i] = 0$ 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 broader district is a suitable instrument – *but only once we have removed spatial correlation in the unobserved determinants of property prices.*

This approach is reasonable if we know what variables to include to get rid of $m(u|c_i, h_i)$ 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):

$$\ln P_i - m(\ln P|c_i, h_i) = \beta[x_i - m(x|c_i, h_i)] + \boldsymbol{\gamma}'[\mathbf{z}_i - m(\mathbf{z}|c_i, h_i)] + v_i \tag{3}$$

$$x_i - m(x|c_i, h_i) = \boldsymbol{\delta}'[\mathbf{z}_i - m(\mathbf{z}|c_i, h_i)] + \sigma v_i + \varepsilon_i - m(\varepsilon|c_i, h_i). \tag{4}$$

This transformation gets around 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 (2) $m(x|c_i, k_i)$, representing spatial impacts at location c_i that operate from beyond those implied by $m(x|c_i, h_i)$ The difference $m(x|c_i, k_i) - m(x|c_i, h_i)$ between these spatial lagged values of crime rates then provides a suitable instrument.

Otherwise, an Instrumental Variables procedure requires exclusion restrictions on $\mathbf{z}_i$ 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.[1] There is little reason to believe that victimisation rates in commercial and residential premises will be related, except through *shifts* in the local supply of crimes. In Section 4.3 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 β. First, 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. Second, we use crimes on non-residential properties as instruments for crimes at or near the property. Next, we estimate the model of (3). To do this we need first to estimate $m(\xi|c_i, h_i)$, 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

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

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 postcoded in 1999 (Home Office, 2000). Property based crimes are the easiest to geocode and comparison of total figures in the dataset with published figures suggests that we have around 98% of the burglaries and 94% of the criminal damage incidents.

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 of reporting 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 disaggregation. 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 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 10,464 properties in the Inner London Area, covering the E, EC1, N, NW, SE, SW, W and WC Postcode Areas,[2] 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 encoded zero, 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.[3] Our final sample with matched grid references amounts to just over 8,000 properties.

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 the 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, the distance is doubled, to compensate for the lower density of non-residential properties.

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 focus of our work is on recorded crimes in the categories *Burglary in a Dwelling*, and *Criminal Damage to a Dwelling*.

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

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

[3] 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. Dropping observations with any missing data leads to less precise estimates but does not change the basic story.

Table 1
Summary Statistics

	Mean	s.d.	Min/Max	*N*
Property prices, 12/00-07/01 (£000)	235.4	244.8	14/4500	8,084
Criminal damage in a dwelling (km^{-2})	50.5	30.5	0.63/155.8	8,084
Burglary in a dwelling (km^{-2})	121.6	79.4	1.2/565.3	8,084
National Grid Reference Eastings	53091	676	51470/54840	8,084
National Grid Reference Northings	18064	664.6	16690/19590	8,084

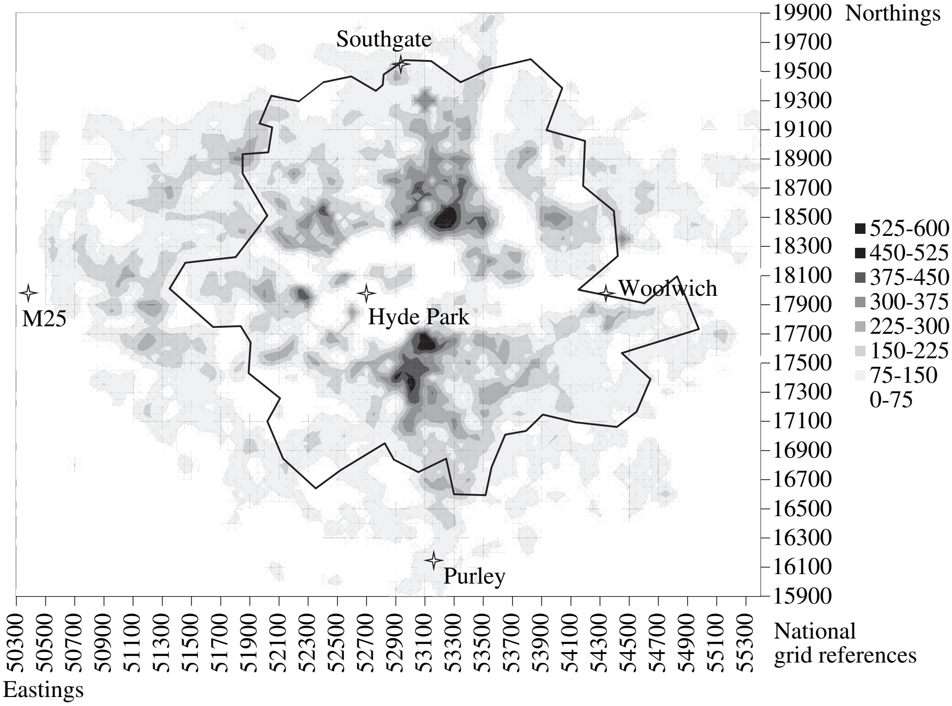

Fig. 1. *Incidents of Burglary in a Dwelling per km², April 1999–March 2000* (regression adjusted for household density)

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.

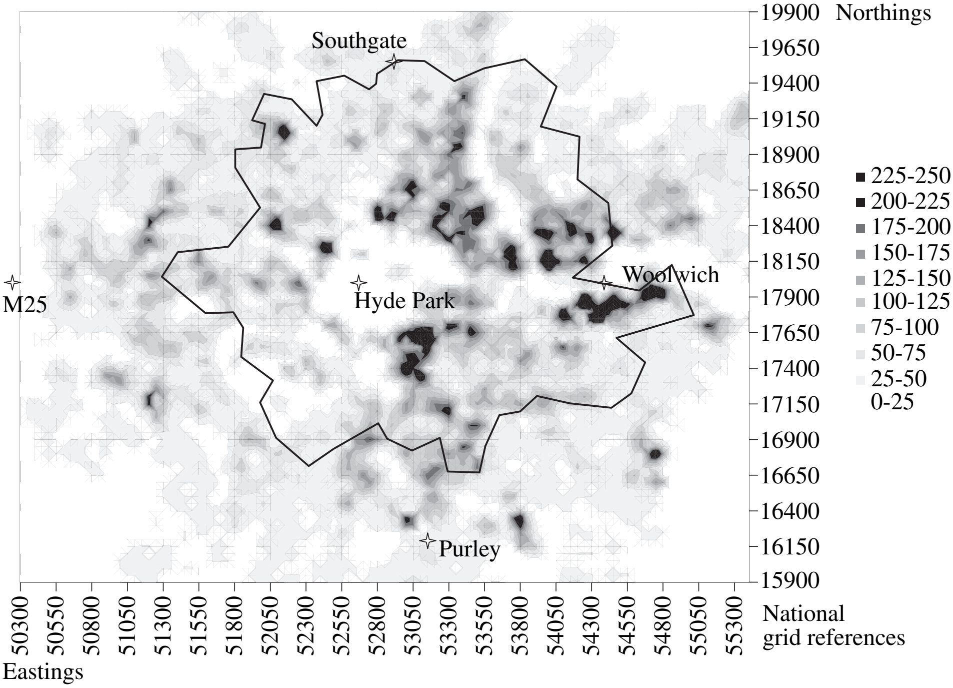

Fig. 2. *Incidents of Criminal Damage to Dwellings per km^2, April 1999–March 2000* (regression adjusted for household density)

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 $m(u|c_i, h_i)$ as it appears in (1) (for details of how this is constructed see Appendix A). The semi-parametric approach employed here removes this spatial variation from the data, 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*

The main estimates in this paper are regression estimates of the models in (1) and (3), taking into account the endogeneity of crimes implied by (2) and (4). These results are shown in Table 2. First, it is worth noting the basic correlations of log prices and crime density in London. The coefficient in a regression of log prices on Criminal Damage density is −0.324 (t = −3.55), but the coefficient in a regression of log prices on Burglary density is 0.100 (t = 3.21). This positive raw association of prices with burglary rates highlights the issue of crime endogeneity described in Section 2.1: the returns to crime are higher in high-price areas, so burglary rates are higher. The regressions presented in Table 2 deal with this issue

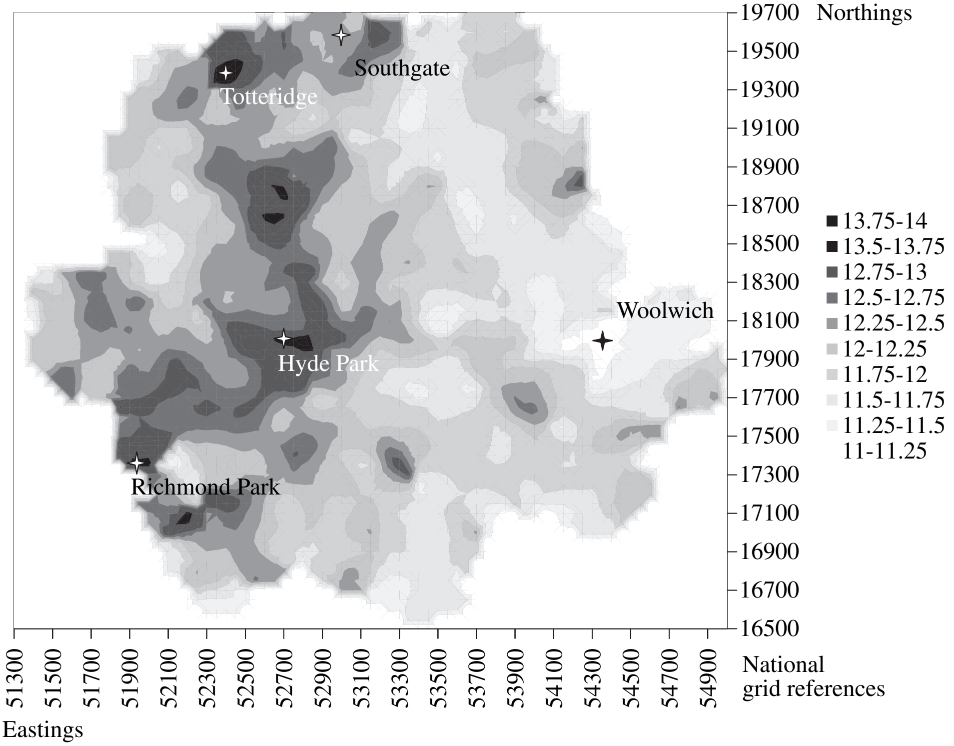

Fig. 3. *Log Property Prices, First 6 Months of 2001*

in various ways. Let us begin though with standard OLS log-property price regressions in Column (1). The semi-log specification is standard in the hedonic literature but we have confirmed this functional form it is acceptable using kernel smoothing. The 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). 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.[4] Crime density could proxy for housing and population density. For presentational reasons we report only the crime coefficients here. The full results are in Appendix C.

Focusing now on our crime incidence variables, the first coefficients in Column (1) suggest a highly significant 3.8% (= exp (-0.768×0.05) -1) decrease in property prices for an additional five reported incidents of Criminal Damage per square kilometre per year. Five incidents is 10% of the sample mean, or an expected 1 additional reported incident per year within a radius of 250m.

[4] 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.

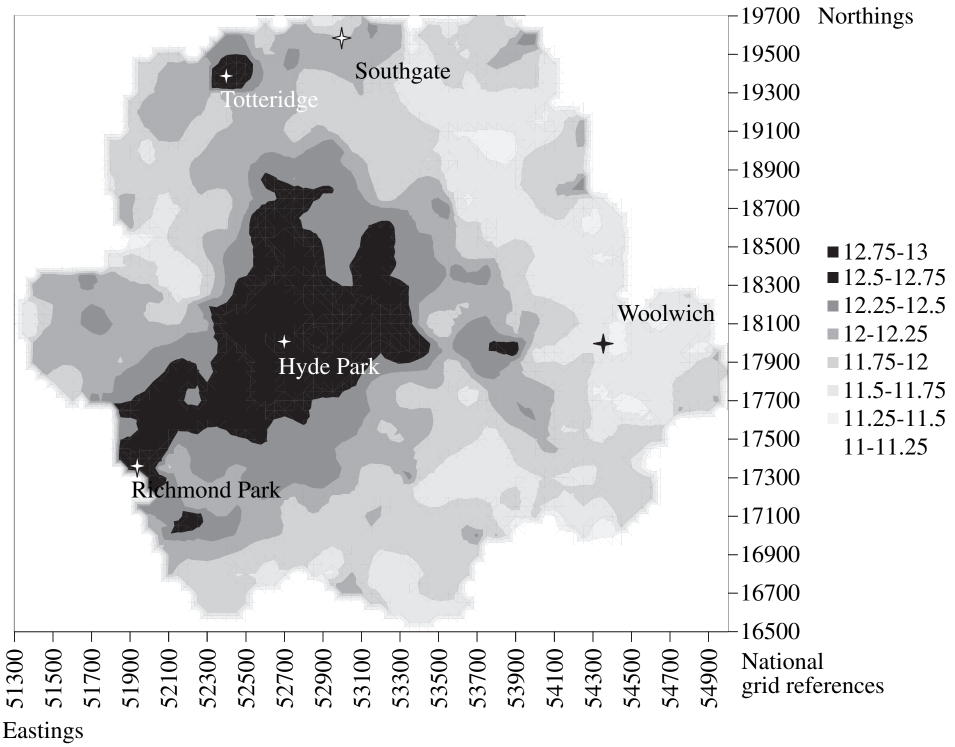

Fig. 4. *Residual Log-Property Price Surface*

However, the association of prices and burglary density is positive, just as we found in the simple single-regressor estimates. Following the discussion in Section 2.1, we assume that 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.[5] Column (2) introduces more neighbourhood and amenity controls. Immediately, the coefficient on Criminal Damage is halved and the impact of Burglaries vanishes to insignificance. This is not an artefact induced by the inclusion of both crime measures in the regression: the coefficient on burglary density is statistically insignificant, and the coefficient on criminal damage significantly negative even if the variables are included separately.

Turning now to an Instrumental Variables approach, Column (3) uses predictions of crimes on dwellings, estimated from the reported incidence of Criminal Damage and Burglaries to other buildings. These IV estimates will be consistent even if victimisation rates or the propensity to report crimes depend on the characteristics of dwellings or households. In fact, the IV point estimate is slightly

[5] 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	IV1	OLS	OLS	IV2	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*	0.088 (4.03)	0.014 (0.71)	0.012 (0.01)	0.014 (0.06)	8.0e-03 (0.45)	0.070 (1.65)	1.22
Housing Controls	Yes	Yes	Yes	Yes	Yes	Yes	
Housing Density	Yes	Yes	Yes	Yes	Yes	Yes	
Neighbourhood and Amenities	No	Yes	Yes	No	Yes	Yes	
Distance to CBD	Yes	Yes	Yes	No	No	No	
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	8,084	8,064	8,064	8,084	8,064	8,064	

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 Postcode Districts. Instruments are: IV1. Density of criminal damage and burglary in other buildings; IV2. 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.

Full results are in Appendix D.

higher than the OLS estimate, but not significantly so using a standard Hausman test of exogeneity ($\chi_1^2 = 0.583$, p-value = 0.445).

In any property value model we must worry about the impact of unobserved local amenities. Columns (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, which may be because the OLS estimates are positively biased by a higher propensity to report amongst owners of high-value properties. In any case, we cannot reject the equality of the OLS and IV Criminal Damage coefficients in Columns (5) and (6) (p-value = 0.452 in the Hausman test).

Adding more community characteristics into the regressions makes little difference. We do not tabulate the results but they are largely insensitive to the inclusion of local school performance and unauthorised school absences. 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.

What is clear from all these specifications is that local incidents of Criminal Damage depress house prices, whilst burglary and prices are *not* related – once allowance is made for the higher returns to crime in higher-price property. Let us adopt the results in Column (5) in Table 2, since this is the most robust specification. A five-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 1.5% (= exp $(-0.31 \times 0.050) -1$). This is quite a substantial impact considering that the mean number of incidents is 50.5, with a standard deviation of 30.5 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 visible crime density leads to a 0.94% decrease in property prices (= exp $(-0.31 \times 0.031) -1$). Interpreting the coefficient as an implicit price in a hedonic function gives us a mean implicit price of around £2,200 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 4.4.

4.3. *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[6] from a property or neighbourhood should be unaffected by the

[6] 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 1 km of the observation.

Table 3

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)*	−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.
*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.

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 3. 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.

There is perhaps still some concern about the magnitude of the Criminal Damage coefficient. Could we be picking up area-deprivation effects, despite the careful empirical implementation so far? Well, 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). One study in a 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 US 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 0.10 g/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, impairs judgement, decreases inhibitions or occasionally induces psychotic disorders (Cooper, 1999). 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 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).

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.[7]

In the lower panel of Table 3 we exploit this result and use distance to the nearest licensed premises, and its polynomials, as instruments for criminal damage in our property price equation. Clearly, pub-proximity is only a valid instrument for criminal damage if it has no direct effect on prices. So, we make the assumption that any direct amenity effects from public house access can be captured in the regressions by local public-house density – that is that households may like a range of local pubs in their neighbourhood but are unconcerned about the distance the nearest. The results indicate that this is appropriate, with an additional 10 pubs or wine bars per km^2 increasing prices by 2.8%, but with no direct effects from nearest-pub distance.

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. There is no evidence here that the estimate of the impact of Criminal Damage on house prices is biased by unobserved area effects.

4.4. *Interpretation and Discussion*

The impression from all these results is that 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 are 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 £19,000 with serious wounding carrying total costs of £130,000. For robbery the figure is £9,700 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

[7] 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.

Table 4

Association Between Year on Year Changes in Police Force Area Crime Rates, 1997–9

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

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.[8] 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 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 4 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 are included to take out general trends. The issue we want to explore is whether Criminal Damage is correlated with other types of crime, conditional on Burglary rates. Certainly, it seems that 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. But only Robbery, Vehicle and Sexual crimes show significant associations with Criminal Damage, *conditional* on Burglary rates. Our price effect of Criminal Damage might reflect household attitudes to these crimes. However, the Total Crime count[9] shows no correlation with Criminal Damage once Vehicle Crime is excluded from the total (Table 4, Column (4), bottom panel).

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*),

[8] Crime data are collected at Local Authority Level, but not for the Criminal Damage category.
[9] i.e. 'Total' excluding Criminal Damage and Burglary.

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.[10] But a square kilometre in Inner London holds, on average, some 2,800 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 £100,000 for an incident of criminal damage.[11] 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*a*), although only 10% of these considered it had a negative impact on their quality of life. Nevertheless, in the same study, 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

[10] The average cost of an additional 14 crimes in one year in one km^2 = exp $[(0.14 \times 0.310) - 1] \times £235{,}000 \times 0.05 = £522$, assuming the coefficient on crimes in 100s per km^2 per year is 0.31, mean property price = £235,000, discount rate = 0.05

[11] 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 1 km^2 containing 2,800 households is $2800 \times £37 \approx £104{,}000$.

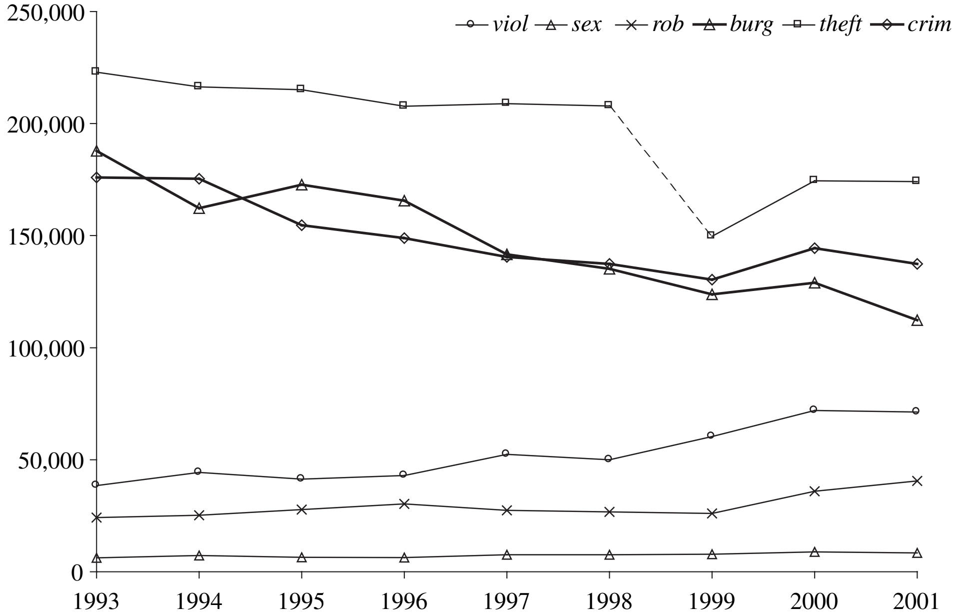

Fig. 5. *Crime Trends in Metropolitan Police Force Area, 1993–2001*
Changes in counting rules can make comparison between pre and post 1999 figures misleading. Figures are adjusted for overall effect on offence groups, but the Theft and Handling group cannot be corrected accurately. All vehicle-related 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.

advocates of neighbourhood cleanup campaigns[12] – 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 or 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

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

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.

5. Conclusion

This paper provides estimates of 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 £2,200 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. The Instrumental Variables estimates, using a variety of alternative instruments, suggest the figure may be even higher. By comparison the Safer Communities Initiative offers Crime and Disorder Reduction Partnerships in the London region[13] a total of £3.7 million for 2002/2003 (Home Office, 2001*c*), or around £1.40 per household.

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 offered 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.

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Appendix A: Computing Locally Weighted Averages

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

$$\hat{m}(\xi|c_i, h_i) = \left[\sum_{j\neq i} \xi_j \phi\left(d_{ij}h^{-1}\right)\right]\left[\sum_{j\neq i} \phi\left(d_{ij}h^{-1}\right)\right]^{-1} \quad (5)$$

[13] 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.

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

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

where $\phi(\cdot)$ 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 $m(\xi|c_i, h_i)$ is thus a kernel-weighted nearest neighbour smoother. This is a variation on the Smooth Spatial Effects Estimator of Gibbons and Machin (2003).

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 $m(\ln p_i|c_i, h_i)$.

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 $m(u|c_g, h)$, 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 (3) to obtain estimates of the linear parameters β, γ. Note now that

$$m(u|c_g, h) = \mathrm{E}\left(\ln p_i - \boldsymbol{\beta}'\mathbf{x}_i - \boldsymbol{\gamma}'\mathbf{z}_i|c_g\right). \tag{8}$$

So we then compute the residuals $\ln P_i - \boldsymbol{\beta}'\mathbf{x}_i - \boldsymbol{\gamma}'\mathbf{z}_i$. Next we calculate the locally weighted averages of these residuals within 2.5 km of each map grid point, using a Gaussian distance decay function (or kernel).

Appendix C: Full Results from Main Regressions

Table A1

London Property Prices and Property Crimes, 2001

	No spatial effects						Smooth spatial effects						
	OLS		OLS		IV1		OLS		OLS		IV2		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*	0.088	(4.03)	0.014	(0.71)	0.012	(0.01)	0.014	(0.06)	8.0e-03	(0.45)	0.070	(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 (1000s m^2)	0.003	(2.86)	0.004	(3.73)	0.004	(3.74)	0.004	(2.91)	0.004	(4.29)	0.004	(4.30)	0.15
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 (100s years)	0.021	(−8.18)	0.015	(7.54)	0.015	(7.66)	0.019	(9.47)	0.016	(8.45)	0.016	(8.30)	0.77
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)	−0.009	(−4.65)	−0.009	(−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	0.004	(3.52)	0.003	(2.67)	0.003	(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	–		−0.003	(0.32)	−0.001	(−0.12)	–		−0.009	(−0.63)	−0.007	(−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	8,084		8,064		8,064		8,084		8,064		8,064		
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 Postcode Districts. Instruments are: IV1. Density of criminal damage and burglary in other buildings; IV2. 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.

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