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PERSONAL INDEBTEDNESS, COMMUNITY CHARACTERISTICS AND THEFT CRIMES

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Personal indebtedness, community characteristics and theft crimes

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Abstract

Becker (1968) and Stigler (1970) provide the germinal works for an economic analysis of crime, and their approach has been utilised to consider the response of crime rates to a range of economic, criminal and socioeconomic factors. Until recently however this did not extend to a consideration of the role of personal indebtedness in explaining the observed pattern of crime.

This paper uses the Becker (1968) and Stigler (1970) framework, and extends to a fuller consideration of the relationship between economic hardship and theft crimes in an urban setting. The increase in personal debt in the past decade has been significant, which combined with the recent global recession, has led to a spike in personal insolvencies. In the context of the recent recession it is important to understand how increases in personal indebtedness may spillover into increases in social problems like crime.

This paper uses data available at the neighbourhood level for London, UK on county court judgments (CCJ's) granted against residents in that neighbourhood, this is our measure of personal indebtedness, and examines the relationship between a range of community characteristics (economic, socio-economic, etc), including the number of CCJ's granted against residents, and the observed pattern of theft crimes for three successive years using spatial econometric methods.

Our results confirm that theft crimes in London follow a spatial process, that personal indebtedness is positively associated with theft crimes in London, and that the covariates we have chosen are important in explaining the spatial variation in theft crimes. We identify a number of interesting results, for instance that there is variation in the impact of covariates across crime types, and that the covariates which are important in explaining the pattern of each crime type are largely stable across the three periods considered in this analysis.

JEL classification: R1; K42; C11; C21

Keywords: Spatial econometrics; Theft crime; Personal debt default; Economic conditions

1 Introduction

It is well recognised in the economics literature that borrowing plays an important role in household consumption decisions, as Zeldes (1989) demonstrated in testing the permanent income hypothesis. Meanwhile, one of the conclusions of the literature stemming from Becker (1968) on the relationship between unemployment and crime, is that an increase in unemployment ought to be associated with increases in crime, as the unemployed seek to maintain their consumption levels; a voluminous literature has tested whether this relationship holds (see for example: Cantor & Land (1985), Reilly & Witt (1992), Osborn et al. (1992), Pyle & Deadman (1994), Elliott & Ellingworth (1998), Carmichael & Ward (2001)).

Meanwhile, the sociology and criminology literature has made clear that any complete theory of crime has to capture both the criminal *motivation* effect and the criminal *opportunity* effect. One of the main difficulties with understanding the relationship between unemployment and crime has been to disentangle the impact of increased unemployment in an area in terms of the motivation and opportunity components. Increased unemployment reduces legitimate income, increasing the attractiveness of illicit sources of income, but at the same time increased unemployment in an area is likely to reduce criminal opportunity in that area due to increased numbers of residents staying at home or otherwise not being away from the area during working hours.

There is a more fundamental difficulty though with the existing literature, specifically the proposition that increased unemployment will lead to increased crime; that it ignores the important role, understood in the wider economics literature, of borrowing in consumption smoothing. The idea that an individual becomes unemployed and then seamlessly turns to crime as a substitute source of income, seems unrealistic. A more believable proposition, is that an individual, facing economic hardship which reduces legitimate income, would first seek to run down their savings, then would borrow money from institutional and even informal sources in order to support their current consumption, and only when their savings have been exhausted and they are liquidity constrained, might they resort to illicit sources of income to support their consumption needs.

In this sense, a better predictor for the relationship between economic hardship and crime is a measure of personal indebtedness which is based on debt default. In this paper we utilise just such a measure, and using spatial econometric methods we test the association between debt default and theft crimes in London, UK using neighbourhood data for three successive years[1]. Our model allows us to capture a range of both criminal *motivation* and criminal *opportunity* effects, as well as the important role played by spatial heterogeneity within the city-region, in explaining the observed pattern of theft crimes.

2 Motivation

The global recession beginning in 2008 led to an increase in unemployment, decreases in wages, and increases in debt default in many countries. In the decade prior to the 2008 recession there was a huge increase in personal debt in many countries, including in the UK and USA (as Figure 4 illustrates). Since 2008 there has been a reduction in the level of outstanding consumer credit, however it has only returned to 2005 levels in the UK and 2006 levels in the USA. Given the huge increase in personal debt in the preceding decade, it is perhaps little surprise that following the start of the 2008 recession we saw an increase in personal insolvencies in the UK and the USA. Figure 5 shows the spike in personal insolvencies in England & Wales since 2008, and in personal bankruptcies in the USA from 2006[2].

Against the backdrop of unprecedented levels of consumer debt and spikes in personal insolvencies, the question arises whether there is any relationship between increases in the number of theft crimes observed and increases in personal debt default. Unfortunately, we do not currently have neighbourhood level personal indebtedness data for the period of the recent recession. However, if the level of personal indebtedness in a given community is indeed an important factor in explaining theft crime levels in that community, and in neighbouring communities, evidence found in support of this relationship in economically good times is

[1] We do not utilise panel data spatial econometric models at this stage because of data constraints which we hope to overcome in the future. However, there are studies which use these kinds of models to examine crime rates, a recent example is Benoit (2013).

[2] White (2007) explain the sharp decline in non-business bankruptcies in the USA in 2006 as arising from the passage of the Bankruptcy Abuse Prevention and Consumer Protection Act which made "bankruptcy law much less debtor-friendly" (White 2007, 175).

arguably stronger evidence of this relationship than evidence obtained during periods of general economic crisis; which is what this paper seeks to establish. Future work will seek to extend the database to consider the pre and post-2008 period.

It has been frequently recognised in the crime literature that crime is a spatial phenomenon, and that in explaining observed crime rates it is necessary to control for more than simply the characteristics of an area, and to look to the characteristics of neighbouring areas. In our study the starting point for examining the spatial dimension to crime in London, and motivating the use of spatial econometric models, is the maps contained in Figures 1 - 3.

Figure 1 shows the pattern of robberies in London in 2004/05. The map is coloured into 5 quintiles for easy reference with green indicating areas with robbery rates that place them in the lowest quitile and areas shaded red are areas with robbery rates in the highest quintile. It is clear from Map 1 that there is a thick donut of areas with low robbery rates (the darkest green shading) in the areas of London which are furthest from the centre of the city, while the centre of the city has areas with much higher robbery rates. There is a clear spatial pattern to Figure 1.

Figure 2 shows the rate of thefts of cars in 2004/05. Similar to Figure 1 there is a clear pattern to this map with areas surrounding the centre of the city and in particular towards the east of London dominating the areas of high motor vehicle thefts. Neighbourhoods to the west of the centre of London are largely areas with vehicle theft rates in the lowest quintiles. One explanation for the high rates of vehicle thefts surrounding the centre of the city is the presence of ‘park and ride’ facilities in these areas which leads to a huge increase in vehicle numbers during the day, as commuters opt to take public transportation into the centre of London rather than pay the congestion charge.

Figure 3 shows the rate of dwelling burglary in 2004/05. Unlike the previous two maps, in this case there appears to be a wider dispersion of the areas of high crime away from the centre of the city with areas to the north and to the south of the city being the focus for most of the areas in the highest quintile of dwelling burglary. There are areas to the west which are in the top two quintiles for this crime, and the occasional area in the east which features in the top quintiles, but it is clear from Figure 3 that the main areas for dwelling burglary are to the north of the city centre, and to the south of the city centre but across the River Thames.

That all three crimes have a spatial dimension is clear from Figure 1 - 3, although each has a slightly different spatial pattern. The centre of the city appears to be an important 'anchor' around which crime takes place, but for each crime type the spatial focus of criminal activity is different. From these maps, and based on the existing literature, we hypothesis that these crime rates in London follow a spatial process. In order to capture this we use spatial econometric models, but we give no prior favour to any particular spatial model, and instead use Bayesian posterior model comparison techniques to determine the spatial econometric model which best explains each crime type.

3 Literature review

This paper draws on three separate literatures on urban crime: criminology, sociology and economics. In this section we briefly review the main contributions of each of these literatures, with a focus on the key message of each in motivating and understanding the observed pattern of urban crime, which we draw together in the final part of this section.

3.1 Economics literature

Becker (1968) provides the following means of thinking about the rational offenders' decision to commit, or not, a crime. Defining y_0 as the income in the absence of any criminal activity being undertaken by the individual, the payoff from not committing crime is taken as:

$$U_{NC} = u(y_0) \tag{1}$$

If the individual does engage in crime they obtain income y_1 if not apprehended, tried, convicted, and given punishment F, and $y_1 - F$ otherwise; the condition is imposed that $y_1 - F \leq y_1$. We also need to define the probability that the individual is apprehended as p (it is assumed that all individuals who are apprehended are tried, convicted, and punished with certainty). The payoff from committing the crime is therefore equal to $p.(y_1 - F) + (1 - p).(y_1)$; giving an expected utility equal to:

$$EU_C = p.u(y_1 - F) + (1 - p).u(y_1) \tag{2}$$

Crime, under this approach, will not occur (sometimes called the no-crime condition), where:

$$U_{NC} > U_C \tag{3}$$

Becker used this simple model to illustrate how, in the presence of a sufficiently large F and subject to a couple of other conditions[3], p could be very low and crime could be eradicated. Thus costs incurred in maintaining a large p, for instance through law enforcement activity, could be saved. This simple model has provided the basis for a large empirical literature examining different aspects of the economics of crime, most importantly for our purposes is the literature on the relationship between unemployment and crime; since it provides the closest parallel to our discussion of the relationship between financial hardship and crime.

There is a large literature in economics looking at the relationship between economic conditions and crime (see for example Brenner (1971, 1976, 1978), Brenner & Harvey (1978), Cantor & Land (1985), Elliott & Ellingworth (1998), Pyle & Deadman (1994), Reilly & Witt (1992), Osborn et al. (1992), Carmichael & Ward (2001)). Most, if not all, take their theoretical premise from the work of Becker (1968). An important strand of this literature focuses on the relationship between unemployment and crime, and there are mixed findings in this literature; some papers find this relationship to be positive (Reilly & Witt 1992, Osborn et al. 1992, Elliott & Ellingworth 1998, Carmichael & Ward 2001), others find it to be negative (Cantor & Land 1985)[4], while some find no or only weak evidence to support a relationship between unemployment and crime (Pyle & Deadman 1994).

Part of the reason why there is such a large literature in this area is that

[3]These are that individuals are risk neutral or risk averse, and the possibility of sufficiently severe punishments, i.e. F lim $\rightarrow \infty$.

[4]Cantor & Land (1985) find that the relationship between unemployment and crime is initially, and generally, negative, but for some crime types there is a lagged positive effect relating to the increase in the motivation effect.

increased unemployment in an area would likely impact on both sides of Becker's (1968) model. Increased unemployment reduces legitimate income, but equally increased unemployment in an area will be expected to increase the number of people at home during the day. This would likely increase the probability of detection, for at least some types of crimes, in the local area (Osborn et al. 1992). It has now been recognised that both the *motivation* and *detection* components must be captured in the analysis of this relationship. There is an additional complication in this literature, noted by Cantor & Land (1985), that being in employment creates opportunities for individuals to engage in criminal acts.

One difficulty with the Becker (1968) theory itself is that it fails to account for the fact that not all of those who could financially benefit from crime resort to it. This was a point recognised in Reilly & Witt (1992) who appealed to the sociological concept of 'social control' (explained below) in explaining why some individuals resort to crime and others do not. A different approach was taken by Dhami & al Nowaihi (2012) in a recent paper which considered the Becker (1968) model in the context of non-expected utility theory.

This paper is of particular interest in providing a more flexible means of thinking about the decision outlined in Equation 3 above; specifically, their extension of Becker (1968) using rank dependent utility and cumulative prospect theory. It is clear that not everyone who could financially gain from committing a crime commits that crime; the difficulty with the expected utility treatment is that it fails to reflect this reality. The fact that that there exists a class of utility functions which capture the behaviour of individuals in overweighting low probability events, provides a useful means of thinking about the individuals decision about whether or not to commit a crime; better reflecting the observed level of criminality.

The basic idea of cumulative prospect theory is that individuals evaluate decisions based on gains and losses relative to some reference point, and that losses hurt more than equivalent gains; in other words a loss of $100 causes a greater loss in utility than a gain of $100 causes in increased utility. The biggest problem with empirically estimating this class of utility functions is determining the reference point which individuals use in evaluating their options. See Barberis (2012) for a review of prospect theory and its applications.

In our case, where we are evaluating the Becker (1968) models decision whether to commit the crime or not, it is not clear, in general, what reference point an individual would use. However, when evaluating the impact of personal indebtedness it seems obvious that there are no circumstances under which an increase in debt default could be considered a *gain* relative to *any* reference point. In this way we can consider increases in debt default as representing losses relative to the individuals reference point, and thus an increase in crime to offset these losses à la Becker (1968) would be anticipated.

The starting point for Dhami & al Nowaihi (2012) in extending Becker (1968) is the introduction of a probability weighting function (pwf), which they denote $w(p)$. The pwf is used to transform the probabilities in Equation 2 from the linear in probabilities assumption of expected utility. This gives a no crime condition (Equation 3) under rank dependent expected utility as: $\Gamma(p, F) = [1 - w(1 - p)]u(y_1 - F) + w(1 - p)u(y_1) \leq u(y_0)$. The essential point here is that expected utility theory predicts a level of crime which does not accord with observed crime levels. However, by introducing probability weighting functions, we can derive a utility function which better reflects the decisions individuals make and thus a model which better reflects observed levels of crime.

The popularity of non-expected utility theories of crime lies in their ability to explain why people overweight low probability events, such as the probability of getting caught committing a crime[5]. This is only part of the story though, and the argument has been made before, in relation to tax evasion, that there are reasons beyond simply overweighting the likelihood of small probability events to explain the observed level of compliance with the law.

In one study (Alm et al. 1992) it was shown that in experiments: "compliance is not always due to overweighting or to extreme risk aversion, since there is some compliance when there is no chance of detection and there is some evasion when the expected value of the evasion gamble is negative" (Alm et al. 1992, 36). This suggests that there are other reasons why people comply with laws that aren't due to overweighting the probability of detection if they do not comply; otherwise why

[5] In the UK the probability of being caught and charged after stealing a car has been calculated (for 2002) at around 13%, the probability of then being convicted at around 7%, the chance having been convicted of being sent to jail at around 1% and the odds that you are then sentenced to more than three months in jail at 1 in 200 (see http://www.prnewswire.co.uk/news-releases/car-thieves-enjoy-one-in-200-chance-of-getting-away-with-it-154572235.html)

would they comply when there is no probability of detection?

In order to understand why personal indebtedness motivates a resort to criminality, we rely upon Dhami & al Nowaihi's (2012) extension of Becker (1968) using the cumulative prospect theory of utility developed by Tversky & Kahneman (1992). In addition, in our model we control for some of the 'social' factors which the literature argues are important; for instance population turnover as a proxy for the strength of social bonds. While part of the explanation for the fact that not everybody who could benefit from committing crime does so will lie in an overweighting of small probability events, another part of the explanation is related to the presence of social norms and conventions about which much has been written in the sociology literature, to which we now turn.

3.2 Sociology & Criminology literature

In explaining the level of criminality in an area, sociologists have generally relied upon explanations related to the ecology of the area, the educational attainment of the population, the level of legitimate earnings, etc. In the context of the unemployment-crime relationship raised earlier in the paper, sociologists, such as Box (1987), have emphasised the impact of anomie and a lack of legitimate means for advancement in explaining the decision by those in economic downturns to resort to criminality.

Box (1987) categorises the three schools of thought explaining why those experiencing economic hardship may resort to crime as: strain theory, control theory, and conflict theory. Strain theory and conflict theory are both theories focused on explaining the individual level decision to engage in criminal activity. Strain theory, the name derives from the idea that certain experiences- for instance unemployment- can create 'strain' in the lives of those affected; encompasses the idea that those experiencing financial difficulty become alienated from society and feel relatively deprived, leading to a resort to illicit sources of income. Conflict theory focuses on the role of stereotypes and profiling in driving those affected to conform with the stereotype.

In terms of community characteristics, control theory focuses on the social bonds, or more broadly a sense of community, which acts to reinforce social norms and deter a resort to criminality among those experiencing hardship. Of course the reverse holds and where social bonds are weak, it is anticipated that in response to the same hardship those residing in areas with weaker social ties will be more likely to resort to crime to augment their income. A good proxy for these social norms, and their strength in an area is the extent of population turnover. It is intuitively obvious that it is more difficult to establish social bonds and ties in an area where population turnover is higher[6]. This also relates to the Becker (1968) framework in affecting the expectation of deterrence. In areas with low social ties, and a high degree of turnover in the population, the probability of detection will likely be lower.

To see this, consider that in relation to housebreaking, in areas with low social ties and high population turnover it is less likely that neighbours will be surprised by the presence of strangers or willing to challenge those they do not recognise. In areas with less social chaos and disorganisation, where people know their neighbours and are consequently more likely to challenge the presence of strangers, the probability of detection, and hence p in Equation 2, is expected to be greater.

The criminology literature is vast in this area, but the relationship between economic downturns and crime was well summarised by Farrington et al. (1986): "unemployment causes financial hardship, which in turn causes crime designed to alleviate that hardship..." (Farrington et al. 1986, 335). A similar argument could be made about personal indebtedness, and indeed given that incurring debt may be the first stage of 'coping' for those experiencing financial hardship it is arguable that the presence of personal indebtedness represents an aggravated stage of financial hardship compared to becoming unemployed.

In addition the criminology literature emphasises the importance of ecological determinants of crime, for instance that population density makes certain crimes riskier, for instance housebreaking, as there is an increased probability of detection. For other crimes, such as thefts from the person, the criminology literature tells us that higher population density should be associated with more of these crimes as it increases the potential victims.

[6] Chilton (1964) notes that in a study by Clifford Shaw population change and poor housing (along with TB, adult crime rate and mental disorders) were taken to represent a measure of social disorganisation which were found to be highly correlated with levels of juvenile delinquency.

3.3 Key conclusions from the literature

For our purposes in this paper there are some key issues arising from the literature. The framework from Becker (1968) provides us with a useful means to explain the observed pattern of crime. In order to do so we must control for a range of criminal opportunity (including factors influencing the probability of detection) and criminal motivation effects; for instance the importance of social disorganisation and chaos emphasised in the sociology literature, and the importance of variables such as population density as emphasised in the criminology literature.

It is clear from the literature that the best framework for explaining the observed level of criminality is the non-expected utility versions of Becker (1968) introduced by Dhami & al Nowaihi (2012). While an overweighting of low probability events helps to understand the observed level of criminality, cumulative prospect theory provides an excellent means of thinking about the impact of personal indebtedness on theft crimes. While in applications of cumulative prospect theory there is often some difficulty in determining the appropriate reference point, this is not an issue in extending the Becker (1968) model for our purposes. Relative to *whatever* reference point people use it is hard to see how debt default can be considered anything other than a loss relative to that reference point. In such a scenario a resort to an illicit income source is surely more attractive.

Given that our data here relate to a single city, variations in the punishment levied for different offences are unlikely to be large. Even if, in practice, the disposal of certain offences in certain courts in particular areas- as a result of judicial heterogeneity- does tend to carry a harsher sentence than it would in courts in neighbouring areas, it is unlikely that this is going to be significantly harsher and something which is common knowledge among the population. We outline our modelling approach in the following section.

4 Data & model

We use data from the UK Neighbourhood Statistics website (neighbourhood.statistics.gov.uk) covering a range of economic, crime and socioeconomic variables at the 'super-output' area level in this analysis. There are two 'super-output' area levels; lower and middle, we utilise middle super output area (MSOA) data in this paper. There are 982 MSOA's in London with a minimum resident population of 5,000 people and an average of 7,200.

There are 6 theft crimes considered in this analysis (theft from the person, robbery, burglary of a dwelling, burglary of a non-dwelling, theft from a motor vehicle, and theft of a motor vehicle), of which 3 are presented here, these are: robbery, burglary of a dwelling and theft of a motor vehicle. All crime variables are converted into crime rates (crimes per 1000 people usually resident) using population data.

We include a range of economic and socioeconomic variables to capture both the criminal motivation and criminal opportunity effects defined as important in the literature, these include: income in the area, the level of personal indebtedness in an area, a measure of the quality of the housing in an area, the composition of the population in terms of age (the more children and elderly people, the higher the resident population is likely to be during the day), the population turnover (as a measure of the strength of social ties), and population density (capturing one aspect of the probability of detection).

Two of our variables are only available for the middle year of our analysis (housing in poor condition and average weekly household income). This means that we are assuming that the relative values of these variables between areas in each year is the same. While the use of these variables in the previous and following years' analysis is not ideal, it is the best that can be done given that we are working at a small spatial scale. Our spatial weight matrix is specified on the basis of contiguity.

We estimate the three most common spatial econometric models in our analysis, these are: the spatial error model (SEM) the spatial autoregressive model (SAR) and the Spatial Durbin model (SDM) (see LeSage & Pace (2009) for a textbook exposition of these models). All models are estimated using Bayesian spatial econometric methods with diffuse, relatively uninformative priors specified. Having calculated the three spatial econometric models (SAR, SEM, SDM) we calculate posterior model probabilities to select the best fit model, the results of which we then present. All models are considered equally plausible ex-ante.

Each of these models suggests a slightly different spatial process, and hence motivation. These can be summarised as follows:

- In the SAR model spatial autocorrelation is exhibited in the dependent variable. From an econometric perspective, if the true data generating process (DGP) for the data is the SAR model, and one utilizes, for example, OLS for estimation purposes, the resulting coefficient estimates will be biased and inconsistent due to the endogeneity of the term on the right hand side of the equation (LeSage & Pace 2009). This model suggests that crime rates follow a spatial autoregressive process, and hence crime rates in one area impact on crime rates in neighbouring areas- consistent with the standard crime spillover argument.
- The SEM model posits that the spatial autocorrelation is found in the error term. It is possible that for a variety of reasons, when an econometric model is specified and estimated, certain factors that should be included in the model are not and that these factors are correlated over space, resulting is residual spatial error correlation. If the true DGP is the SEM model and, again for example, OLS is used in the estimation, the OLS estimators of the coefficients are unbiased but inefficient and the estimates of the variance of the estimators are biased (LeSage & Pace 2009).
- The SDM model extends the SAR model by including spatially weighted explanatory variables. LeSage & Pace (2009) suggest that the SDM model should be used when one believes that there may be omitted variables that follow a spatial process and are correlated with included independent variables.

5 Empirical results

In this section we recap the results previously presented in McIntyre & Lacombe (2012) and discuss the results from the extended analysis in this paper. This previous work was carried out using fewer explanatory variables, for instance we did not include the proportion of elderly people in the population for each area. In the analysis in this paper we consider a broader range of explanatory variables which we feel better capture the factors which will influence the probability of detection in an area.

In our extended results we present, for each theft crime type, a model using the number of CCJs granted in each area as our measure of personal indebtedness, but we also include a measure of the proportion of these which are of valued at over £1000 and also a measure of those which are valued at less than £251. In our earlier work we focussed on the total value of CCJs as our measure of personal indebtedness, however in order to investigate whether the distribution of the value of CCJs matters in explaining theft crime rates, we needed to use the number of CCJs as our initial measure of indebtedness in this analysis. In the results which follow we calculate 95% and 99% credible intervals, and where the interval does not include 0, i.e. the credible intervals have the same sign, these are considered significant at the appropriate level. Coefficients with a '*' after them in Tables 2 - 4 are those which are considered significant at the 95% level.

5.1 Results from McIntyre & Lacombe (2012)

Table 1 presents the regression results published in McIntyre & Lacombe (2012). In interpreting these results, we need to first explain the distinction between the *direct* and *indirect* effects. The *direct* effects are the impact of our explanatory variable in that area on our dependent variable in that area; for instance the impact of income in Shoreditch on robbery rates in Shoreditch. The *indirect* effect is the impact of the explanatory variable in one area, on the dependent variable in neighbouring areas; for instance the impact of income in Shoreditch on robbery rates in Bethnal Green (see LeSage & Pace (2009) for more on this).

These results demonstrate a number of things; firstly the importance of spatially modelling crime data, secondly the importance of personal indebtedness in explaining the observed pattern of theft crimes, and also the consistency of these results with economic, criminal and sociological theories of crime. To pick out a couple of results; we can see from Table 1 that poor quality housing is positively and directly associated with all crime types, this is consistent with an ecological view of crime. Areas with poor housing provide better opportunities for burglary, are likely to be poorer quality neighbourhoods more generally (for instance by being poorly lit, making personal theft crimes easier), and it is also likely that poor quality housing will be associated with poorer quality motor vehicles which are easier to steal.

Income meanwhile is negatively associated with robbery, non-dwelling burglary and theft of a motor vehicle. To take thefts of a motor vehicle, it makes sense that richer people will have better motor vehicles which are more difficult to steal, and therefore higher income areas would see fewer thefts of cars. In richer areas it is also likely that non-dwellings will be rarer, and thus burglaries of non-dwellings in this area will be less frequent.

In terms of personal indebtedness, the value of CCJs is positively associated, both directly and indirectly, with robbery and theft from the person, this suggests that where personal indebtedness is high in an area, personal thefts are higher in that area and in neighbouring areas. These crimes are, arguably, two of the least 'skilled' theft crimes possible and thus could be considered 'entry level offenses', which would be consistent with the notion of individuals turning to crime in response to economics hardship. Housebreaking and car theft are relatively 'skilled' crimes which are likely to be beyond the abilities of those turning to crime in the face of economic hardship, as opposed to those for whom criminality is a more routine activity.

Building on these results there are certain features which we want to examine further in this paper. While we have included a measure of personal indebtedness in our initial regression results, we are interested to understand whether the importance of personal indebtedness in explaining crime patterns varies according to the size of the debt. In addition, and focussing on the issue of deterrence and the probability of detection, we also include here a measure of the proportion of the population which is elderly. Finally, given that population turnover is taken as a proxy for the strength of social ties, we experiment with different measures of population turnover.

5.2 Further results

Tables 2-4 present the initial results from our spatial econometric analysis of three types of crime in London for the years 2003 to 2005[7]. We have again, as is standard in the spatial econometrics literature, calculated the direct, indirect and total effects estimates for each variable. We calculate the mean effects and the 95% and 99% credible intervals for each variable, and where the credible interval does not contain zero, it can be considered statistically significant at that level. The spatial coefficient in all our models is highly significant, with the credible interval not spanning zero, verifying that the crime rates being modelled follow a spatial process.

Taking our results in turn, from Table 2 we can see that for robberies our results for all three years are largely consistent. The only difference is that only in 2003 is the proportion of CCJs valued at greater than £1000 is positively associated with robberies both directly (i.e. within that neighbourhood) and indirectly (in neighbouring areas). Poor housing condition is positively associated with robberies in all years, which as before is consistent with the ecological explanation for crime. Otherwise, in all years the variables which capture the probability of detection (net changes in population and population density) are negative and significant, suggesting that weak social ties and population density are related to fewer robberies in that area.

For population density, this conclusion differs from previous work which suggests that for personal theft crimes, such as robbery, population density is positively associated with these crimes; the argument being that the higher the population density the greater the potential victims. In initial work for the North East of England region we found this relationship to be negative and significant. We will explore this issue further as part of our future activities; looking simply at the raw data on population densities shows that the London city-region and the North East England region have vastly different scales for population density and so perhaps this offers some explanation for our different findings.

In terms of the motivation components, we can see that income is negatively as-

[7] A shortage of time in preparing this manuscript is the only reason for the absence of the results for the other crime types.

sociated with robberies in all years, while the proportion of males in the population and the net inflow of males aged 16 to 24 are positively associated with robberies in the area, and in neighbouring areas. In terms of personal indebtedness, as expected, the greater personal indebtedness, the greater number of robberies which are observed in that area (directly) and in neighbouring areas (indirectly). These results are consistent with our earlier findings and with our prior expectations based on the existing literature.

One thing to note before continuing, is that we included the % of OAPs in the population and the % of the population which is aged 0-15 in order to capture differences in the population of an area during the day (our belief being that the more young children and OAPs in an area the higher the daytime population of an area and hence the lower the levels of crime). In the case of robberies, neither of these variables is significant. However, this makes sense to us, as robberies are not the type of crime for which people being at home during the day are likely to increase the detection and hence deterrence effect, unlike car thefts and home burglaries to which we now turn.

Turning to Table 3 we can see that, again, there is a high degree of consistency over time in explaining thefts of motor vehicles. Higher income is associated with fewer theft of cars (perhaps because richer people purchase cars which are more difficult to steal), while housing in poor condition is positively associated with thefts of cars (perhaps because poor quality housing is correlated with poor quality cars which are easier to steal).

In the case of thefts of cars, the proportion of OAPs (old age pensioners) in the population is negatively associated with thefts of cars. As we said earlier, we included the % of OAPs in the population in our model to capture the deterrence effect of people being at home during the day. Given that in a city such as London a high proportion of commuters travel by public transport, leaving cars at home, it makes sense that the greater the proportion of elderly people in an area the greater the probability of detection while stealing a car in that area.

Some variables are important only in 2003 and 2005, for instance the net inflow of 15 to 24 year olds, we have no intuition for this inconsistency over time, but we do note that where it is significant it accords with our expectations in being positively associated with thefts of motor vehicles. In all years the number of

CCJs granted in an area is positively associated with thefts of motor vehicles in that area and in neighbouring areas, as expected.

In the final set of results in Table 4, our results are more varied across the three years. Certain results are consistent over time, these are: that greater population density is negatively associated with home burglaries, that the greater the net inflow of 15 to 24 year olds the greater the number of burglaries, that the more houses in poor condition the more burglaries- as would be expected- and finally that the greater the proportion of the population which are children (aged 0-15) the fewer burglaries which occur. These are all in line with our expectations regarding criminal motivation and opportunity.

The greater the population density in an area, the greater the risk of detection when breaking into a home. So we would expect, and we find in our results, that the higher the population density is in an area, the fewer burglaries of dwellings that take place in that area. The more young children in an area the higher the occupancy rate of homes during the day and hence the greater the probability of detection when breaking into a dwelling, which explains why- in all years -the higher the share of children in the population the lower the rate of home burglaries. In the case of the % OAPs this is only significant in the middle year, but it similarly suggests that the more elderly people the lower the rate of housebreaking which accords with our prior expectations and theory.

The number of CCJs granted in an area is positively and significantly associated with burglaries in the first two years, but not 2005, although in 2004 and 2005 the proportion of CCJs valued at less than £251 is significantly and positively associated with house burglaries in that area. In terms of the indirect results, the impact on neighbouring areas, in each period there is a positive and significant impact of one or more of our measures of personal indebtedness on burglaries of dwellings in neighbouring areas.

In terms of the income variable, we see that income in an area is positively associated with house breaking in that area. This would be expected in the sense that the richer the area, the more valuable the potential loot. However, we also see that income is negatively related to burglaries in neighbouring areas, which again makes sense and captures the criminal motivation effect. To explain this point, note that this result means that the lower the income in areas neighbouring area

'A' the greater the rate of house breaking in area 'A'. If the potential loot from housebreaking is taken to be a function of income, then if income in neighbouring areas is lower than in area 'A', criminals in neighbouring areas may travel to the higher income area (area 'A') to break into homes; this would explain the negative indirect effect income coefficient[8].

6 Conclusion

This paper has analysed the relationship between a range of economic and socioeconomic variables and three theft crime for London in the year 2003 to 2005. We have seen that there is broad consistency between our results for all three years of this analysis. We have also seen, again, the important role of personal indebtedness in explaining the observed pattern of theft crimes. Building on the earlier analysis in McIntyre & Lacombe (2012) we have extended to consider both the preceding and succeeding years data, but also a broader range of covariates. Our results reinforce the findings of McIntyre & Lacombe (2012) and extend them in a useful manner.

Future research will seek to employ panel data spatial econometric methods to further explore this urban crime relationship; there are data issues which are impeding this research at the moment, but which we hope to overcome in the future. In addition, we are seeking to expand our database to include data for subsequent years. Of particular interest is the period covering the recent global recession. We have also explored a comparison of these results across the urban hierarchy, in other words comparing different types of regions, and the consistency of the results obtained here, in that context. Again, we are somewhat limited in terms of the geographic coverage of our data at the neighbourhood level, but this remains an important future topic of research.

[8] Benoit (2013) motivates his crime analysis for Chicago, USA using routine activity theory, and the idea that individual potential criminals move routinely over space to identify opportunities to commit crimes. Our results here could also be interpreted in this context.

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Figure 1: Robbery Rate 2004-05

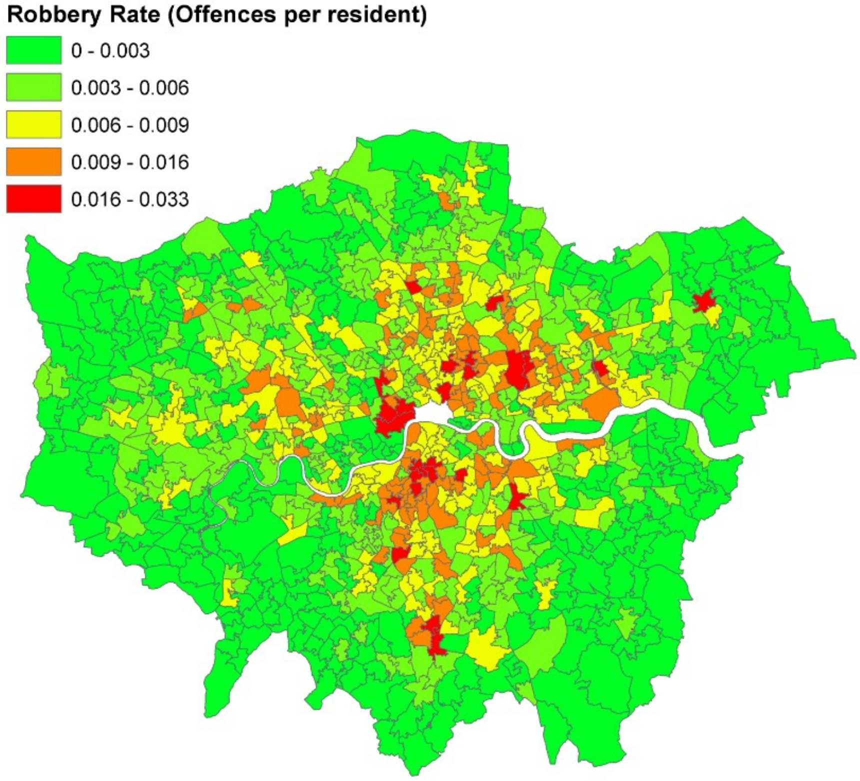


Figure 2: Theft of Motor Vehicle Rate 2004-05

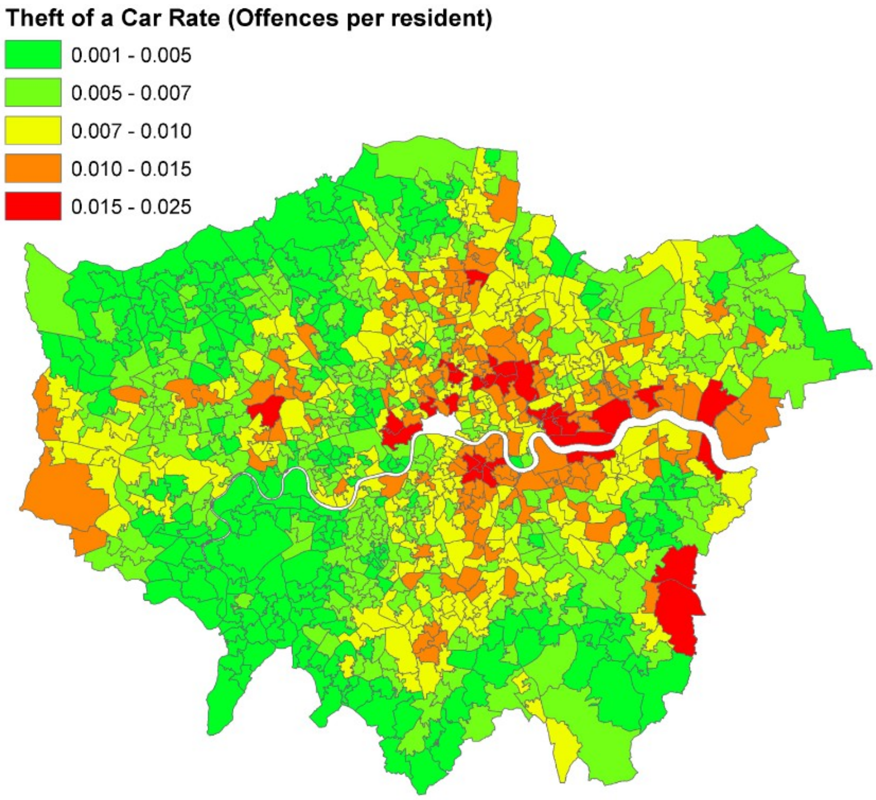
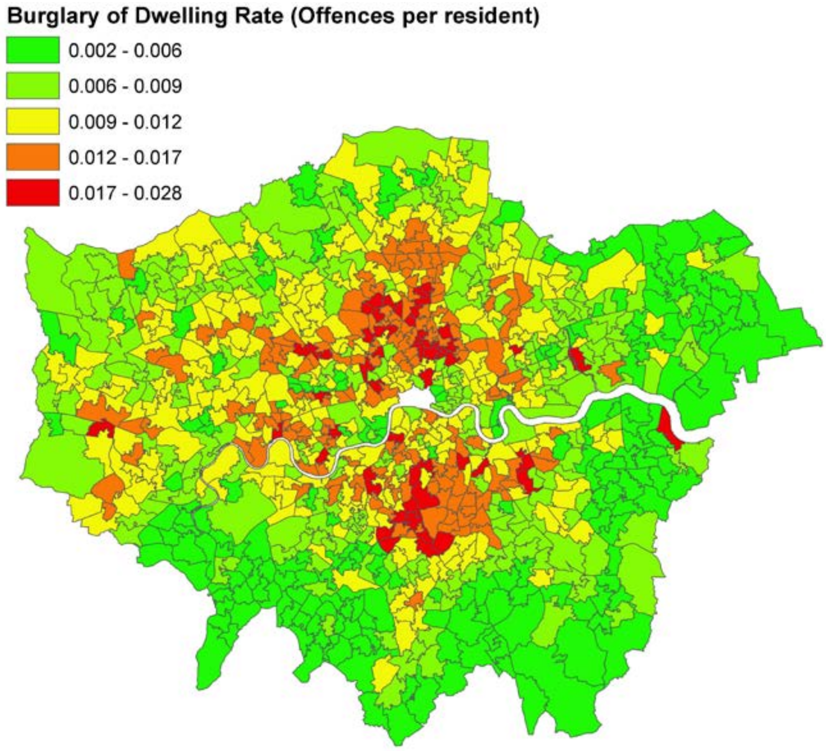
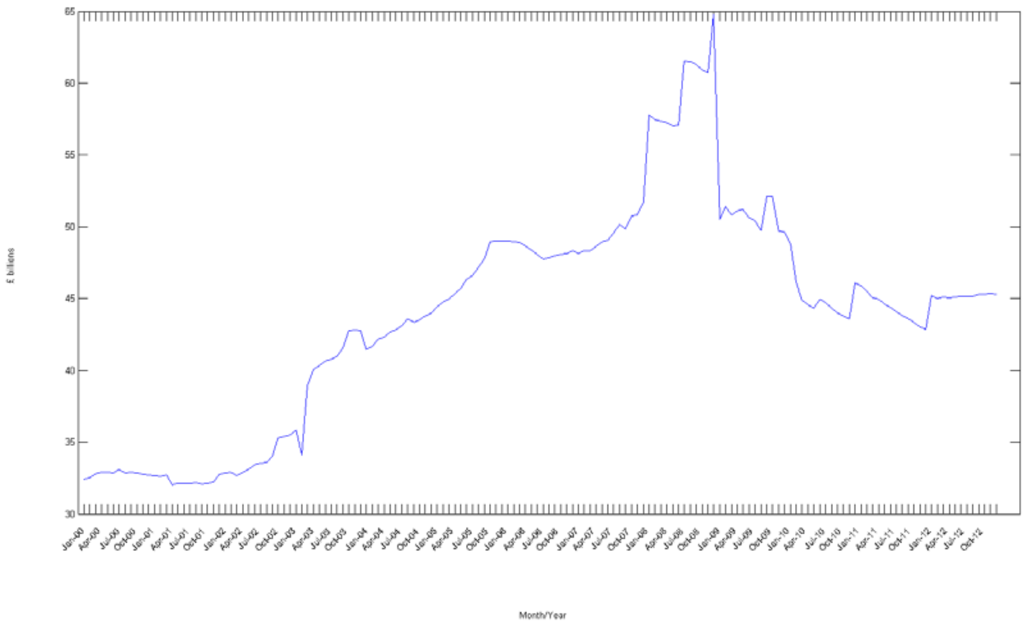


Figure 3: Burglary Rate 2004-05





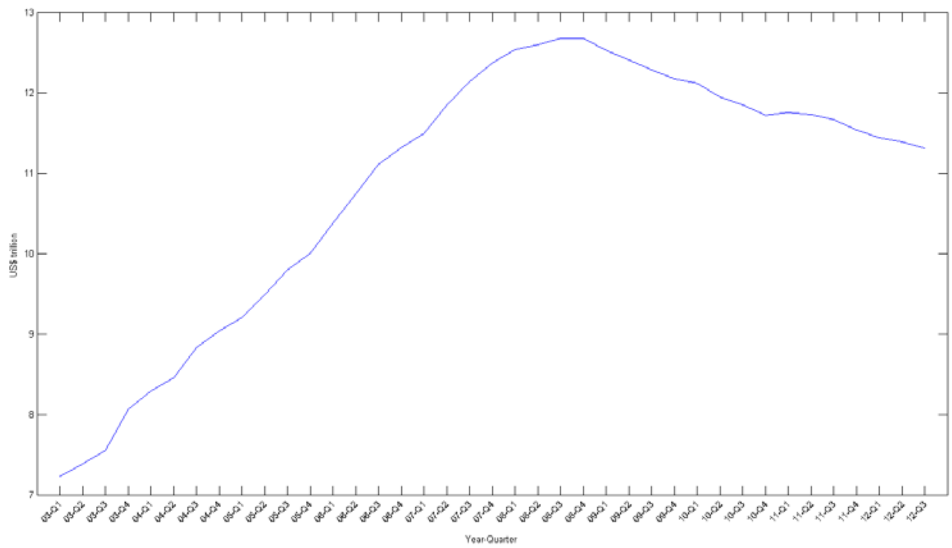


Figure 4: Consumer credit in the UK (Monthly amounts outstanding of other consumer credit lenders (excluding the Student Loans Company) net unsecured lending to individuals (in sterling millions) seasonally adjusted. Source: Bank of England.) and USA (USA Total Household Debt Balance. Source: New York Federal Reserve).

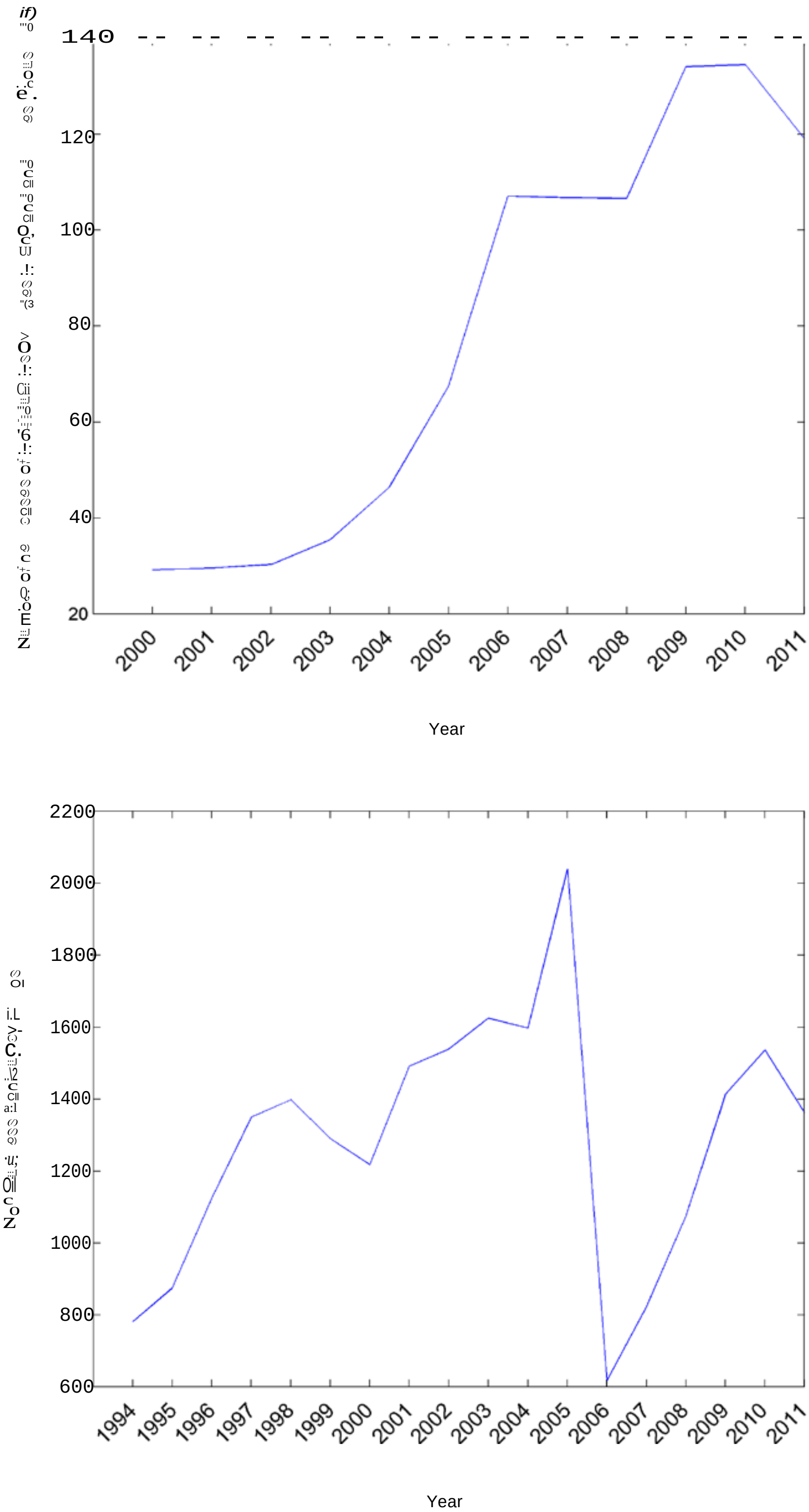


Figure 5: Total individual insolvencies iwEngland and Wales (Source: The Insolvency Service) and US non-business bankruptcy (Source: American Bankruptcy Institute).

Table 1: Results from McIntyre & Lacombe (2012)

Direct Effects

Variable[a]	Total theft crime Mean	Lower 95%	Upper 95%	Robbery Mean	Lower 95%	Upper 95%	Thefts from the person Mean	Lower 95%	Upper 95%	Burglary (dwelling) Mean	Lower 95%	Upper 95%	Burglary (non-dwelling) Mean	Lower 95%	Upper 95%	Theft of a motor vehicle Mean	Lower 95%	Upper 95%	Theft from a motor vehicle Mean	Lower 95%	Upper 95%
Total value of CCJ	0.042409*	0.014861	0.070862	0.052907*	0.008218	0.098538	0.028842*	0.013721	0.044395	0.048024	-0.005206	0.101342	0.021826	-0.006259	0.05222	0.045246	-0.005248	0.098555	0.021859	-0.015282	0.060759
Population turnover	-0.029125	-0.058312	0.000484	-0.093255*	-0.140468	-0.046402	-0.017263*	-0.031742	-0.00341	-0.018755	-0.075204	0.037628	0.032034*	0.001167	0.063877	0.051031	-0.004437	0.105769	-0.057141*	-0.104119	-0.008691
% pop 0-15	-0.114694*	-0.148144	-0.081403	-0.088632*	-0.135958	-0.042599	-0.049357*	-0.065379	-0.032595	-0.137225*	-0.195804	-0.079955	-0.114743*	-0.150685	-0.079409	-0.005737	-0.060739	0.048788	-0.093292*	-0.14504	-0.04002
% pop 16-24	0.018417	-0.016	0.052798	0.032295	-0.013548	0.078957	0.018358	-0.000483	0.038344	0.012747	-0.041144	0.063968	-0.008921	-0.048649	0.031807	-0.014946	-0.066877	0.036644	-0.013851	-0.064036	0.03708
Houses in poor condition	0.152809*	0.116301	0.189254	0.20791*	0.15427	0.261198	0.036598*	0.018556	0.054413	0.193533*	0.13133	0.255762	0.148241*	0.107559	0.190581	0.207798*	0.147848	0.268447	0.147422*	0.085791	0.208878
Income	-0.03769	-0.075318	0.000913	-0.128778 *	-0.177162	-0.080843	-0.010277	-0.028143	0.007479	-0.005129	-0.066846	0.055478	-0.060871*	-0.10126	-0.019853	-0.245493*	-0.307307	-0.185489	0.026041	-0.035965	0.087888
Pop. Density	-0.177331*	-0.217521	-0.137664	-0.091997 *	-0.143314	-0.042226	-0.032506*	-0.05226	-0.012719	-0.043521	-0.10747	0.020301	-0.25308*	-0.294356	-0.211345	-0.186242*	-0.245536	-0.127107	-0.271474*	-0.335681	-0.208146

Indirect Effects

Variable	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%
Total value of CCJ	0.03027	-0.064107	0.125438	0.064071*	0.009897	0.124665	0.046423*	0.00807	0.086611	0.083663	-0.00901	0.18338	0.047797	-0.046854	0.143328	0.086674	-0.009904	0.196037	-0.039542	-0.224977	0.151226
Population turnover	-0.032902	-0.129242	0.060832	-0.112871	-0.181201	-0.054052	0.010928	-0.028677	0.050772	-0.032603	-0.135117	0.065999	0.087987	-0.010236	0.195263	0.097699	-0.008374	0.209876	0.063163	-0.14587	0.266374
% pop 0-15	0.033088	-0.072075	0.136377	-0.107261*	-0.171413	-0.049548	0.017512	-0.026219	0.058783	-0.239208*	-0.367988	-0.131043	0.134628*	0.027995	0.24467	-0.011077	-0.115981	0.094577	0.125105	-0.088696	0.34125
% pop 16-24	0.00223	-0.088924	0.095647	0.039001	-0.016007	0.097283	0.026522	-0.013042	0.067815	0.02219	-0.071789	0.116781	0.105958*	0.005514	0.214597	-0.028573	-0.130178	0.069938	0.070643	-0.110926	0.263204
Houses in poor condition	-0.012914	-0.124976	0.097443	0.251731*	0.174024	0.34523	-0.043823*	-0.085887	-0.001158	0.337228*	0.212912	0.485507	-0.121784*	-0.234722	-0.009861	0.397924*	0.265552	0.560172	-0.056926	-0.28305	0.168528
Income	-0.097335	-0.205243	0.008271	-0.155991 *	-0.228858	-0.092079	0.024979	-0.016828	0.065115	-0.009183	-0.116569	0.097782	0.036346	-0.068749	0.137673	-0.47025 *	-0.646394	-0.326188	-0.001648	-0.212181	0.209213
Pop. Density	0.301043*	0.199629	0.406187	-0.11136*	-0.182301	-0.049584	0.130996*	0.0897	0.173463	-0.075664	-0.196053	0.035964	0.258524*	0.152672	0.360941	-0.357022 *	-0.514398	-0.225429	0.653776*	0.434052	0.879784

Total Effects

Variable	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%	Mean	Lower 95%	Upper 95%
Total value of CCJ	0.072679	-0.029645	0.176041	0.116978*	0.0185	0.222306	0.075265*	0.032473	0.119657	0.131687	-0.014592	0.284613	0.069622	-0.032393	0.173414	0.131921	-0.015347	0.292484	-0.017683	-0.218271	0.188776
Population turnover	-0.062027	-0.166735	0.044188	-0.206126*	-0.318855	-0.101496	-0.006335	-0.048145	0.037132	-0.051358	-0.210776	0.103303	0.120021*	0.015022	0.236338	0.148731	-0.012825	0.312239	0.006022	-0.21991	0.225781
% pop 0-15	-0.081606	-0.188514	0.025931	-0.195893*	-0.303853	-0.092583	-0.031845	-0.075931	0.009959	-0.376433*	-0.561922	-0.212301	0.019886	-0.091	0.132119	-0.016814	-0.176892	0.143858	0.031813	-0.193935	0.259488
% pop 16-24	0.020647	-0.074489	0.118294	0.071296	-0.029426	0.174289	0.044881*	0.00538	0.086997	0.034937	-0.111673	0.181625	0.097037	-0.006125	0.205734	-0.043518	-0.197001	0.105676	0.056792	-0.130624	0.254315
Houses in poor condition	0.139894*	0.025157	0.252945	0.459641*	0.332291	0.597431	-0.007225	-0.050719	0.036665	0.530761*	0.351657	0.737053	0.026457	-0.089578	0.142861	0.605722*	0.415704	0.812854	0.090497	-0.149321	0.330016
Income	-0.135025*	-0.24287	-0.031073	-0.284769	-0.400252	-0.17424	0.014702	-0.024698	0.053437	-0.014312	-0.184738	0.154637	-0.024525	-0.128925	0.078867	-0.715742	-0.940366	-0.519905	0.024393	-0.19026	0.240794
Pop. Density	0.123712*	0.020149	0.234847	-0.203357*	-0.324185	-0.092563	0.098489*	0.055735	0.140618	-0.119185	-0.303163	0.055888	0.005444	-0.101712	0.11316	-0.543264*	-0.751249	-0.355928	.382302*	0.155619	0.626589

[a] A '*' next to the mean effect estimate indicates that the variable is considered statistically significant at the 95% level.

Table 2: Results - Robbery

Direct Effects

	2003					2004					2005				
Variable Name[a]	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.2320	-0.2114	-0.1484*	-0.0851	-0.0666	-0.1965	-0.1751	-0.1137*	-0.0533	-0.0304	-0.2155	-0.2005	-0.1369*	-0.0716	-0.0504
Percentage of pop. aged 0-15	-0.1244	-0.1058	-0.0449	0.0169	0.0363	-0.1270	-0.1091	-0.0539	0.0007	0.0186	-0.1318	-0.1169	-0.0581	0.0002	0.0156
Percentage of pop. male aged 0-15	-0.0439	-0.0299	0.0200	0.0699	0.0839	-0.0358	-0.0221	0.0258	0.0770	0.0992	-0.0516	-0.0346	0.0171	0.0719	0.0908
% of males in population	-0.0069	0.0090	0.0658*	0.1205	0.1380	0.0170	0.0324	0.0815*	0.1322	0.1445	0.0114	0.0281	0.0794*	0.1318	0.1477
% OAPs in population	-0.0720	-0.0495	0.0165	0.0808	0.0987	-0.0325	-0.0153	0.0485	0.1108	0.1329	-0.0522	-0.0298	0.0341	0.0988	0.1191
Houses in poor condition	0.1324	0.1494	0.2056*	0.2639	0.2812	0.1292	0.1468	0.2055*	0.2641	0.2811	0.0777	0.1003	0.1579*	0.2167	0.2338
Net change in population	-0.1500	-0.1336	-0.0810*	-0.0268	-0.0106	-0.1376	-0.1229	-0.0719*	-0.0206	-0.0059	-0.1718	-0.1569	-0.1054*	-0.0543	-0.0357
Net inflow 15 to 24	0.0445	0.0689	0.1426*	0.2170	0.2383	0.0226	0.0361	0.0819*	0.1341	0.1540	0.0735	0.0900	0.1530*	0.2318	0.2570
Population density	-0.1589	-0.1430	-0.0902*	-0.0354	-0.0186	-0.1573	-0.1404	-0.0856*	-0.0296	-0.0145	-0.1577	-0.1408	-0.0858*	-0.0277	-0.0096
Number of CCJ's granted	0.0091	0.0291	0.0835*	0.1372	0.1526	0.0202	0.0361	0.0897*	0.1436	0.1605	-0.0031	0.0158	0.0719*	0.1284	0.1472
% of CCJ's valued at greater than 1000	-0.0151	0.0014	0.0478*	0.0954	0.1105	-0.0188	-0.0045	0.0429	0.0898	0.1025	-0.0365	-0.0247	0.0227	0.0706	0.0845
% of CCJ's valued at less than 251	-0.0434	-0.0317	0.0101	0.0518	0.0654	-0.0115	-0.0012	0.0391	0.0812	0.0931	-0.0452	-0.0339	0.0082	0.0510	0.0634

Indirect Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.2493	-0.2173	-0.1414*	-0.0748	-0.0600	-0.2437	-0.2123	-0.1298*	-0.0579	-0.0344	-0.2503	-0.2182	-0.1399*	-0.0707	-0.0479
Percentage of pop. aged 0-15	-0.1249	-0.1041	-0.0428	0.0158	0.0334	-0.1490	-0.1282	-0.0615	0.0007	0.0219	-0.1484	-0.1251	-0.0595	0.0002	0.0165
Percentage of pop. male aged 0-15	-0.0449	-0.0284	0.0191	0.0677	0.0851	-0.0404	-0.0250	0.0294	0.0900	0.1134	-0.0551	-0.0357	0.0174	0.0739	0.0942
% of males in population	-0.0068	0.0089	0.0628*	0.1211	0.1436	0.0188	0.0352	0.0931*	0.1562	0.1776	0.0121	0.0287	0.0811*	0.1401	0.1605
% OAPs in population	-0.0726	-0.0476	0.0156	0.0803	0.0992	-0.0364	-0.0166	0.0553	0.1304	0.1575	-0.0539	-0.0303	0.0346	0.1020	0.1253
Houses in poor condition	0.1093	0.1289	0.1960*	0.2763	0.3091	0.1324	0.1536	0.2347*	0.3284	0.3588	0.0754	0.0968	0.1613*	0.2414	0.2728
Net change in population	-0.1529	-0.1331	-0.0771*	-0.0248	-0.0101	-0.1675	-0.1470	-0.0820*	-0.0230	-0.0066	-0.1936	-0.1706	-0.1078*	-0.0522	-0.0354
Net inflow 15 to 24	0.0424	0.0629	0.1357*	0.2200	0.2503	0.0240	0.0395	0.0934*	0.1593	0.1853	0.0691	0.0880	0.1561*	0.2474	0.2866
Population density	-0.1651	-0.1460	-0.0860*	-0.0318	-0.0168	-0.1968	-0.1691	-0.0979*	-0.0334	-0.0145	-0.1715	-0.1542	-0.0878*	-0.0276	-0.0090
Number of CCJ's granted	0.0080	0.0262	0.0795*	0.1384	0.1560	0.0212	0.0405	0.1024*	0.1710	0.1926	-0.0032	0.0150	0.0735*	0.1367	0.1564
% of CCJ's valued at greater than 1000	-0.0144	0.0012	0.0456*	0.0937	0.1067	-0.0228	-0.0053	0.0490	0.1066	0.1246	-0.0380	-0.0254	0.0231	0.0724	0.0887
% of CCJ's valued at less than 251	-0.0429	-0.0305	0.0096	0.0501	0.0662	-0.0123	-0.0014	0.0447	0.0952	0.1164	-0.0482	-0.0349	0.0084	0.0527	0.0701

Total Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.4733	-0.4235	-0.2897*	-0.1618	-0.1301	-0.4350	-0.3813	-0.2436*	-0.1122	-0.0648	-0.4570	-0.4141	-0.2768*	-0.1440	-0.0986
Percentage of pop. aged 0-15	-0.2480	-0.2074	-0.0877	0.0326	0.0684	-0.2731	-0.2355	-0.1155	0.0014	0.0409	-0.2795	-0.2412	-0.1177	0.0003	0.0321
Percentage of pop. male aged 0-15	-0.0894	-0.0585	0.0391	0.1363	0.1656	-0.0738	-0.0470	0.0552	0.1654	0.2084	-0.1064	-0.0706	0.0345	0.1455	0.1850
% of males in population	-0.0137	0.0181	0.1286*	0.2408	0.2781	0.0359	0.0682	0.1745*	0.2850	0.3179	0.0237	0.0584	0.1606*	0.2689	0.3036
% OAPs in population	-0.1415	-0.0971	0.0322	0.1619	0.1992	-0.0692	-0.0321	0.1038	0.2378	0.2874	-0.1056	-0.0589	0.0687	0.1991	0.2411
Houses in poor condition	0.2483	0.2845	0.4016*	0.5352	0.5763	0.2694	0.3028	0.4402*	0.5802	0.6203	0.1546	0.1988	0.3192*	0.4496	0.4922
Net change in population	-0.2965	-0.2634	-0.1581*	-0.0526	-0.0212	-0.3024	-0.2661	-0.1540*	-0.0445	-0.0126	-0.3586	-0.3231	-0.2131*	-0.1074	-0.0693
Net inflow 15 to 24	0.0867	0.1325	0.2783*	0.4311	0.4805	0.0466	0.0761	0.1754*	0.2907	0.3345	0.1457	0.1800	0.3091*	0.4723	0.5362
Population density	-0.3199	-0.2853	-0.1763*	-0.0682	-0.0349	-0.3485	-0.3062	-0.1836*	-0.0637	-0.0290	-0.3275	-0.2923	-0.1736*	-0.0551	-0.0186
Number of CCJ's granted	0.0165	0.0556	0.1630*	0.2726	0.3050	0.0418	0.0771	0.1921*	0.3106	0.3476	-0.0063	0.0315	0.1455*	0.2610	0.2978
% of CCJ's valued at greater than 1000	-0.0291	0.0025	0.0934*	0.1875	0.2130	-0.0411	-0.0098	0.0919	0.1945	0.2244	-0.0741	-0.0499	0.0458	0.1431	0.1696
% of CCJ's valued at less than 251	-0.0844	-0.0625	0.0197	0.1018	0.1326	-0.0228	-0.0026	0.0838	0.1749	0.2055	-0.0907	-0.0675	0.0167	0.1025	0.1342
R-squared	0.4243					0.4180					0.4003				
Rbar-squared	0.4177					0.4114					0.3935				

[a] A '*' next to the mean effect estimate indicates that the variable is considered statistically significant at the 95% level.

Table 3: Results - Theft of a Car

Direct Effects

	2003					2004					2005				
Variable Name[a]	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.3168	-0.2938	-0.2270*	-0.1612	-0.1394	-0.2834	-0.2591	-0.1877*	-0.1147	-0.0948	-0.3609	-0.3361	-0.2648*	-0.1903	-0.1657
Percentage of pop. aged 0-15	-0.1113	-0.0916	-0.0379	0.0157	0.0329	-0.1313	-0.1146	-0.0563	0.0031	0.0207	-0.0703	-0.0520	0.0061	0.0666	0.0866
Percentage of pop. male aged 0-15	-0.1333	-0.1174	-0.0702*	-0.0239	-0.0116	-0.1057	-0.0921	-0.0399	0.0116	0.0266	-0.1302	-0.1159	-0.0609*	-0.0078	0.0092
% of males in population	-0.0813	-0.0662	-0.0144	0.0380	0.0512	-0.1222	-0.1070	-0.0518	0.0037	0.0213	-0.0904	-0.0718	-0.0183	0.0350	0.0549
% OAPs in population	-0.1820	-0.1605	-0.0918*	-0.0267	-0.0073	-0.2285	-0.2042	-0.1327*	-0.0593	-0.0370	-0.2033	-0.1803	-0.1103*	-0.0403	-0.0180
Houses in poor condition	0.0702	0.0874	0.1492*	0.2089	0.2313	0.0370	0.0594	0.1283*	0.1938	0.2182	0.0828	0.1038	0.1654*	0.2277	0.2501
Net change in population	-0.1199	-0.1020	-0.0484	0.0049	0.0209	-0.0754	-0.0579	-0.0009	0.0566	0.0789	-0.0342	-0.0183	0.0382	0.0958	0.1150
Net inflow 15 to 24	0.0655	0.0910	0.1632*	0.2229	0.2405	-0.0495	-0.0349	0.0147	0.0732	0.0950	-0.0036	0.0166	0.0809*	0.1458	0.1639
Population density	-0.3166	-0.2960	-0.2388*	-0.1842	-0.1631	-0.3095	-0.2917	-0.2348*	-0.1766	-0.1588	-0.3340	-0.3163	-0.2575*	-0.1989	-0.1839
Number of CCJ's granted	0.0539	0.0691	0.1209*	0.1746	0.1925	0.0247	0.0428	0.1068*	0.1694	0.1903	-0.0066	0.0147	0.0738*	0.1345	0.1540
% of CCJ's valued at greater than 1000	-0.0606	-0.0453	0.0044	0.0524	0.0670	-0.0814	-0.0623	-0.0067	0.0469	0.0667	-0.0506	-0.0344	0.0183	0.0717	0.0870
% of CCJ's valued at less than 251	-0.0533	-0.0381	0.0066	0.0499	0.0639	-0.0547	-0.0392	0.0088	0.0566	0.0749	-0.0195	-0.0023	0.0446	0.0921	0.1087

Indirect Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.5922	-0.5305	-0.3716*	-0.2476	-0.2129	-0.5478	-0.4902	-0.3273*	-0.1897	-0.1507	-0.5589	-0.5075	-0.3665*	-0.2492	-0.2152
Percentage of pop. aged 0-15	-0.1892	-0.1560	-0.0620	0.0257	0.0555	-0.2470	-0.2094	-0.0981	0.0054	0.0387	-0.0977	-0.0733	0.0085	0.0942	0.1270
Percentage of pop. male aged 0-15	-0.2382	-0.2059	-0.1151*	-0.0392	-0.0182	-0.2004	-0.1638	-0.0694	0.0198	0.0463	-0.1918	-0.1649	-0.0843*	-0.0110	0.0134
% of males in population	-0.1445	-0.1111	-0.0236	0.0613	0.0888	-0.2333	-0.1962	-0.0905	0.0066	0.0387	-0.1272	-0.1006	-0.0253	0.0474	0.0751
% OAPs in population	-0.3231	-0.2742	-0.1504*	-0.0421	-0.0111	-0.4458	-0.3819	-0.2318*	-0.0998	-0.0618	-0.3009	-0.2608	-0.1527*	-0.0558	-0.0225
Houses in poor condition	0.1101	0.1373	0.2442*	0.3651	0.4191	0.0648	0.1031	0.2237*	0.3600	0.4257	0.1038	0.1373	0.2289*	0.3362	0.3707
Net change in population	-0.2004	-0.1746	-0.0792	0.0079	0.0351	-0.1404	-0.1055	-0.0015	0.1032	0.1397	-0.0469	-0.0253	0.0530	0.1367	0.1654
Net inflow 15 to 24	0.0980	0.1441	0.2673*	0.3965	0.4379	-0.0880	-0.0608	0.0255	0.1289	0.1706	-0.0046	0.0228	0.1117*	0.2083	0.2423
Population density	-0.5864	-0.5286	-0.3910*	-0.2746	-0.2477	-0.6304	-0.5621	-0.4097*	-0.2799	-0.2454	-0.5234	-0.4829	-0.3565*	-0.2497	-0.2187
Number of CCJ's granted	0.0852	0.1066	0.1980*	0.3070	0.3518	0.0390	0.0732	0.1863*	0.3149	0.3568	-0.0095	0.0199	0.1023*	0.1941	0.2269
% of CCJ's valued at greater than 1000	-0.1000	-0.0765	0.0071	0.0859	0.1115	-0.1461	-0.1091	-0.0116	0.0826	0.1167	-0.0700	-0.0477	0.0253	0.1011	0.1235
% of CCJ's valued at less than 251	-0.0918	-0.0625	0.0108	0.0827	0.1083	-0.0971	-0.0695	0.0155	0.0997	0.1386	-0.0281	-0.0030	0.0620	0.1356	0.1606

Total Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.8846	-0.8144	-0.5986*	-0.4140	-0.3573	-0.8144	-0.7439	-0.5150*	-0.3068	-0.2423	-0.9035	-0.8292	-0.6312*	-0.4470	-0.3872
Percentage of pop. aged 0-15	-0.2996	-0.2464	-0.0999	0.0415	0.0894	-0.3716	-0.3223	-0.1543	0.0082	0.0599	-0.1674	-0.1250	0.0146	0.1597	0.2129
Percentage of pop. male aged 0-15	-0.3708	-0.3193	-0.1853*	-0.0633	-0.0305	-0.3031	-0.2530	-0.1093	0.0311	0.0723	-0.3169	-0.2785	-0.1452*	-0.0189	0.0229
% of males in population	-0.2240	-0.1765	-0.0380	0.1004	0.1401	-0.3550	-0.3016	-0.1423	0.0102	0.0598	-0.2178	-0.1722	-0.0436	0.0819	0.1310
% OAPs in population	-0.4965	-0.4314	-0.2422*	-0.0676	-0.0187	-0.6650	-0.5784	-0.3645*	-0.1597	-0.0966	-0.4954	-0.4342	-0.2630*	-0.0986	-0.0405
Houses in poor condition	0.1784	0.2249	0.3934*	0.5658	0.6337	0.1036	0.1636	0.3520*	0.5488	0.6320	0.1888	0.2443	0.3943*	0.5625	0.6144
Net change in population	-0.3159	-0.2740	-0.1276	0.0128	0.0574	-0.2133	-0.1605	-0.0024	0.1593	0.2149	-0.0806	-0.0431	0.0913	0.2310	0.2793
Net inflow 15 to 24	0.1648	0.2403	0.4305*	0.6119	0.6612	-0.1364	-0.0959	0.0402	0.2032	0.2587	-0.0082	0.0399	0.1926*	0.3496	0.3939
Population density	-0.8792	-0.8127	-0.6298*	-0.4663	-0.4193	-0.9328	-0.8450	-0.6444*	-0.4646	-0.4085	-0.8425	-0.7922	-0.6140*	-0.4559	-0.4102
Number of CCJ's granted	0.1385	0.1763	0.3188*	0.4747	0.5413	0.0653	0.1172	0.2930*	0.4807	0.5420	-0.0161	0.0352	0.1760*	0.3250	0.3771
% of CCJ's valued at greater than 1000	-0.1576	-0.1221	0.0115	0.1386	0.1806	-0.2264	-0.1717	-0.0182	0.1286	0.1846	-0.1191	-0.0829	0.0436	0.1720	0.2084
% of CCJ's valued at less than 251	-0.1433	-0.1003	0.0174	0.1330	0.1709	-0.1525	-0.1090	0.0244	0.1554	0.2181	-0.0456	-0.0054	0.1066	0.2254	0.2671
R-squared	0.4311					0.4040					0.3977				
Rbar-squared	0.4247					0.3973					0.3908				

[a] A '*' next to the mean effect estimate indicates that the variable is considered statistically significant at the 95% level.

Table 4: Results - Burglary

Direct Effects

	2003					2004					2005				
Variable Name[a]	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.0724	-0.0500	0.0266	0.1021	0.1231	0.0503	0.0684	0.1500*	0.2300	0.2558	0.0673	0.0944	0.1803*	0.2636	0.2857
Percentage of pop. aged 0-15	-0.1865	-0.1665	-0.0988*	-0.0302	-0.0082	-0.3143	-0.2915	-0.2154*	-0.1448	-0.1201	-0.1968	-0.1770	-0.0999*	-0.0231	-0.0008
Percentage of pop. male aged 0-15	-0.1135	-0.0900	-0.0328	0.0283	0.0500	-0.1367	-0.1173	-0.0566	0.0019	0.0213	-0.1332	-0.1112	-0.0466	0.0171	0.0385
% of males in population	-0.1019	-0.0817	-0.0195	0.0431	0.0604	-0.2102	-0.1890	-0.1279*	-0.0681	-0.0513	-0.1017	-0.0835	-0.0201	0.0443	0.0618
% OAPs in population	-0.1659	-0.1415	-0.0634	0.0139	0.0417	-0.1903	-0.1649	-0.0842*	-0.0043	0.0174	-0.0984	-0.0734	0.0105	0.0943	0.1204
Houses in poor condition	0.0317	0.0524	0.1201*	0.1886	0.2069	0.0270	0.0482	0.1230*	0.1979	0.2186	-0.0162	0.0092	0.0870*	0.1665	0.1878
Net change in population	-0.1707	-0.1518	-0.0911*	-0.0283	-0.0097	-0.1354	-0.1164	-0.0562	0.0056	0.0246	-0.1275	-0.1050	-0.0422	0.0237	0.0433
Net inflow 15 to 24	0.0188	0.0346	0.1069*	0.1928	0.2306	0.0394	0.0645	0.1478*	0.2298	0.2642	0.0874	0.1321	0.2388*	0.3504	0.3815
Population density	-0.1623	-0.1424	-0.0791*	-0.0141	0.0086	-0.2209	-0.1962	-0.1221*	-0.0482	-0.0273	-0.1717	-0.1467	-0.0691*	0.0085	0.0355
Number of CCJ's granted	-0.0025	0.0176	0.0761*	0.1370	0.1533	0.0191	0.0412	0.1087*	0.1740	0.1959	-0.0233	-0.0003	0.0718	0.1438	0.1652
% of CCJ's valued at greater than 1000	-0.0706	-0.0498	0.0058	0.0619	0.0810	-0.0192	-0.0017	0.0513	0.1047	0.1211	-0.0826	-0.0663	-0.0093	0.0483	0.0647
% of CCJ's valued at less than 251	-0.0804	-0.0654	-0.0140	0.0341	0.0506	0.0096	0.0253	0.0735*	0.1219	0.1384	0.0015	0.0184	0.0708*	0.1240	0.1386

Indirect Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.1403	-0.0931	0.0492	0.1904	0.2430	-0.9269	-0.8281	-0.5098*	-0.2127	-0.1193	-0.9173	-0.7875	-0.4601*	-0.1529	-0.0508
Percentage of pop. aged 0-15	-0.3722	-0.3269	-0.1829*	-0.0547	-0.0146	-0.6358	-0.5293	-0.2337	0.0366	0.1070	-0.1683	-0.0633	0.2204	0.5126	0.6107
Percentage of pop. male aged 0-15	-0.2113	-0.1736	-0.0607	0.0543	0.0880	-0.2106	-0.1299	0.0820	0.2943	0.3688	-0.3063	-0.2290	0.0120	0.2576	0.3340
% of males in population	-0.2073	-0.1564	-0.0363	0.0805	0.1195	-0.4532	-0.3774	-0.1331	0.0959	0.1729	-0.4469	-0.3484	-0.0882	0.1577	0.2494
% OAPs in population	-0.3259	-0.2714	-0.1175	0.0255	0.0757	-0.6308	-0.5247	-0.2175	0.0749	0.1466	-0.3646	-0.2469	0.0780	0.4167	0.5191
Houses in poor condition	0.0588	0.0924	0.2219*	0.3671	0.4198	-0.0919	-0.0061	0.2714	0.5695	0.6743	-0.1468	-0.0348	0.2853	0.6154	0.7567
Net change in population	-0.3419	-0.2974	-0.1683*	-0.0507	-0.0169	-0.3430	-0.2361	0.0383	0.3125	0.3870	-0.4161	-0.2942	0.0288	0.3532	0.4503
Net inflow 15 to 24	0.0346	0.0618	0.1975*	0.3705	0.4433	-0.4080	-0.3177	-0.0540	0.2087	0.3028	-0.1625	-0.0661	0.2378	0.5778	0.7008
Population density	-0.3222	-0.2762	-0.1460*	-0.0255	0.0154	-0.3292	-0.2555	0.0141	0.2665	0.3406	-0.1420	-0.0592	0.2503	0.5628	0.6682
Number of CCJ's granted	-0.0039	0.0317	0.1408*	0.2641	0.3079	-0.3264	-0.2339	-0.0111	0.2146	0.2885	-0.3708	-0.2859	-0.0238	0.2306	0.3261
% of CCJ's valued at greater than 1000	-0.1315	-0.0929	0.0109	0.1178	0.1562	-0.0454	0.0301	0.2804*	0.5347	0.6174	0.0467	0.1178	0.3648*	0.6293	0.7204
% of CCJ's valued at less than 251	-0.1604	-0.1235	-0.0257	0.0620	0.0938	0.1323	0.2185	0.4737*	0.7548	0.8429	0.1387	0.2224	0.4631*	0.7343	0.8362

Total Effects

	2003					2004					2005				
Variable Name	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%	Lower 99%	Lower 95%	Coefficient	Upper 95%	Upper 99%
Average weekly income	-0.2096	-0.1432	0.0759	0.2928	0.3607	-0.8119	-0.6920	-0.3598*	-0.0403	0.0518	-0.7541	-0.6283	-0.2797	0.0487	0.1405
Percentage of pop. aged 0-15	-0.5489	-0.4904	-0.2816*	-0.0848	-0.0228	-0.8887	-0.7653	-0.4490*	-0.1618	-0.0774	-0.2793	-0.1852	0.1205	0.4338	0.5352
Percentage of pop. male aged 0-15	-0.3215	-0.2606	-0.0935	0.0835	0.1381	-0.2883	-0.2091	0.0254	0.2559	0.3187	-0.3817	-0.2965	-0.0346	0.2302	0.3112
% of males in population	-0.3028	-0.2382	-0.0557	0.1228	0.1781	-0.6012	-0.5158	-0.2610*	-0.0161	0.0710	-0.4829	-0.3900	-0.1083	0.1575	0.2396
% OAPs in population	-0.4780	-0.4120	-0.1808	0.0396	0.1173	-0.7407	-0.6385	-0.3016	0.0186	0.1004	-0.3854	-0.2609	0.0886	0.4476	0.5747
Houses in poor condition	0.0928	0.1463	0.3420*	0.5538	0.6097	0.0056	0.0933	0.3944*	0.7157	0.8176	-0.0904	0.0266	0.3722*	0.7268	0.8686
Net change in population	-0.5038	-0.4481	-0.2593*	-0.0797	-0.0258	-0.4449	-0.3219	-0.0179	0.2847	0.3747	-0.4921	-0.3730	-0.0134	0.3373	0.4483
Net inflow 15 to 24	0.0546	0.0964	0.3045*	0.5645	0.6705	-0.3113	-0.2155	0.0938	0.4009	0.4968	-0.0030	0.1064	0.4766*	0.8678	1.0251
Population density	-0.4795	-0.4144	-0.2250*	-0.0396	0.0240	-0.4721	-0.4007	-0.1080	0.1633	0.2388	-0.2390	-0.1420	0.1812	0.5130	0.6213
Number of CCJ's granted	-0.0064	0.0486	0.2169*	0.3958	0.4572	-0.2438	-0.1431	0.0976	0.3412	0.4161	-0.3094	-0.2225	0.0480	0.3194	0.4045
% of CCJ's valued at greater than 1000	-0.2002	-0.1422	0.0167	0.1781	0.2368	-0.0203	0.0504	0.3316*	0.6137	0.7064	0.0110	0.0933	0.3556*	0.6427	0.7311
% of CCJ's valued at less than 251	-0.2380	-0.1878	-0.0397	0.0961	0.1461	0.1708	0.2636	0.5472*	0.8530	0.9511	0.1697	0.2697	0.5338*	0.8238	0.9444
R-squared	0.2742					0.4023					0.3443				
Rbar-squared	0.2660														

[a] A '*' next to the mean effect estimate indicates that the variable is considered statistically significant at the 95% level.