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PERSONAL INDEBTEDNESS, SPATIAL EFFECTS AND CRIME

BY

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Personal Indebtedness, Spatial Effects and Crime

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Abstract

There is a long and detailed history of attempts to understand what causes crime. One of the most prominent strands of this literature has sought to better understand the relationship between economic conditions and crime. Following Becker (1968), the economic argument is that in an attempt to maintain consumption in the face of unemployment, people may resort to sources of illicit income. In a similar manner, we might expect ex–ante, that increases in the level of personal indebtedness would be likely to provide similar incentives to engage in criminality. In this paper we seek to understand the spatial pattern of property and theft crimes using a range of socioeconomic variables, including data on the level of personal indebtedness.

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Keywords: Spatial Econometrics, Crime, Personal Debt, Economic Conditions

JEL Codes: R1, K42, C11, C21

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1 Introduction

The recent global recession has brought the issue of the relationship between economic conditions and crime to the fore of public and scholarly debate. There has been extensive scholarly work attempting to understand the causes of crime (Kelly 2000, Wilson & Herrnstein 1985, Cohen & Felson 1979, Kvalseth 1977, Danziger 1976). Particularly interesting has been the study of the relationship between unemployment and crime (Carmichael & Ward 2001, Pyle & Deadman 1994, Cantor & Land 1985, Becker 1968). In this paper, we use spatial econometric methods to examine an aspect of the relationship between economic conditions and crime that, to our knowledge, has gone unremarked upon to date; namely the relationship between personal indebtedness and crime. While there are spatial crime regressions in the literature[1], for instance Anselin et al. (2000), Cracolici & Uberti (2009) and Buonanno et al. (2012), little attention is paid to the insights that can be gained by considering the *direct* and *indirect* effects[2] in the context of crime analysis.

2 Material and methods

Given the geographic nature of crime data (Schmid 1960, Voss & Petersen 1971), it is reasonable to suspect that spatial autocorrelation may be an issue when modelling crime data. Spatial autocorrelation can pose problems when using standard econometric techniques, such as OLS (LeSage & Pace 2009). Therefore we propose using Bayesian spatial econometrics methods in this paper (see LeSage & Pace (2009) for a textbook outline of these models and methods). There are three standard spatial econometric models, the spatial autoregressive (SAR) model, the spatial error (SEM) model, and the spatial Durbin model (SDM). The motivation for each model is noted below:

- 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).

[1]Although Buonanno et al. (2012, 194-195) argues that these methods are still rarely utilised by those economists studying crime issues.

[2]The *direct* effect, can be considered the 'within area' effect. The *indirect* effect can be considered the impact of a change in the explanatory variable in one area, on the dependent variable in neighbouring areas. The *total* effect is the sum of the direct and indirect effects.

- 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 spatial Durbin 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.

Our motivation for using Bayesian spatial econometric techniques, as opposed to the more familiar maximum likelihood paradigm, is that Bayesian methods allow us to make non-nested model comparisons in a statistically coherent manner, where model choice proceeds by choosing the model (i.e SAR, SEM or SDM) with the highest posterior probability. In each case we ran the Gibbs sampler for 5000 draws with a 'burn-in' of 500 draws. Homoskedastic and heteroskedastic versions of each of the 3 models (SAR v. SEM v. SDM) were considered, and proper, but relatively uninformative priors were used in all cases.

In this paper we use data for London, UK covering 2004/05 and consider 6 theft crimes: robbery, theft from the person, burglary in a dwelling, burglary of a dwelling, theft of a motor vehicle and theft from a motor vehicle. Personal indebtedness is measured using data on the value of county court judgements (CCJ's) granted in each neighbourhood. Full variable details are provided in Table 2. All variables used here were studentized. The Office of National Statistics (hereafter, ONS) provides statistics at several geographical levels. All data used here are provided at the super output area level which are fixed geographical areas constructed by the ONS at two principle levels: middle and lower and we utilise the middle layer here (each of these areas has a minimum of 5000, and an average of 7,200, people within it).

3 Theory/Calculation

While there has been much written on the crime-unemployment relationship (Carmichael & Ward 2001, Pyle & Deadman 1994, Cantor & Land 1985, Becker 1968) nothing, to our knowledge, appears in academic journals about the relationship between personal indebtedness and crime.[3] Becker (1968) argued that crime, from an economic perspective, stemmed from the inability of individuals to satisfy their target level of consumption through legitimate means (a similar argument was made by Cantor & Land (1985, 317)). The unemployed then, theory suggests, turn to illicit income streams to meet the shortfall in their consumption needs.

Others in the literature, for instance Box (1995), emphasise the emotional strain of becoming unemployed, and the feelings of anomie that stem from the lack of legitimite means for advancement. Additional sociological issues such as the ecology of the local area (Voss & Petersen 1971) and the degree of education (Ehrlich 1975) are also thought to be important determinants of crime. This line of inquiry maintains that, since everyone who suffers economic hardship does not resort to criminality, there must be a reason why some people do and others do not.

We suggest that it is possible to view personal debt as providing the initial means of consumption smoothing following economic hardship. Whereas, in the case of the relationship between crime and unemployment, the view in the literature is almost of a seemless transition from employment to unemployment and an attraction to criminality. However, there could be an important intermediate role to be played by personal debt. An individual made unemployed may seek to access credit as a means of bridging the initial consumption gap, and it is only when they can access no more credit and have defaulted on their existing loans, that they are driven to commit crime to access an illicit income stream a lá Becker (1968).

4 Results & Discussion

The first thing to note is that in all our regression models the spatial autocorrelation coefficient is significant, indicating that spatial autocorrelation is present in the data for all crime categories considered, justifying the use of spatial econometric methods. In our spatial regressions analyses, we used a contiguity weight matrix for each of the three standard spatial econometric models defined earlier in this paper[4]. The second thing to note is that, as previous studies have found, for instance Cantor & Land (1985) and Cherry & List (2002), we find that the explanatory variables that are important in explaining the observed pattern of crime vary across crime type, requiring the use of disaggregated crime measures.

[3] A number of papers written in the 1970's in the United States addressed the general impact of economic crises on crime, see Brenner (1971, 1976, 1978), Brenner & Harvey (1978), Cohen & Felson (1979).

[4] LeSage & Pace (2010) demonstrate that the exact specification of the weight matrix makes little difference in the interpretation of changes in the explanatory variables on the dependent variable as long as the effects estimates are properly calculated.

A brief note about Table 1 may be helpful to the reader. For each of the seven categories of crime[5], recall that we only present the results from the spatial econometric model, for each crime type, which has the highest posterior probability–the model selected for each crime type is noted in row 2 of Table 1. For each model, following LeSage & Pace (2009), we calculate the direct, indirect and total effect of each explanatory variable[6]. The *direct* effect, can be considered the 'within area' effect. The *indirect* effect can be considered the impact of a change in the explanatory variable in one area, on the dependent variable in neighbouring areas. The *total* effect is the sum of the direct and indirect effects.

In motivating this article we made specific reference to both the spatial dimension of this study, and our focus on the role of personal indebtedness. Taking these in reverse order, we can see from our results that personal indebtedness has an important role to play in explaining the observed pattern of personal theft crimes in London, UK. In the case of Robbery, we find that the level of personal indebtedness in an area is positively related to Robbery in that area and in surrounding areas. We obtain the same result for 'thefts from the person'; an offence which differs from that of Robbery only in the degree of violence used. For the other theft crime measures considered, the level of personal indebtedness in an area is not found to be associated with the dependent variable.

Just as the importance of personal indebtedness, noted a moment ago, varies across crime type, the same is true of other explanatory variables. A good example of this is our finding that income is directly and negatively associated with thefts *of* cars, **but**, is not significantly associated with thefts *from* cars. A plausible explanation for this is that in areas with higher incomes, cars have more sophisticated alarm and immobilser systems and are therefore harder to steal. Stealing from a car meanwhile, is perhaps as easy for a more expensive car as an inexpensive car.

Just as important as the distinction between different types of crimes and the explanatory variables that are important in explaining them, is the *direct* and *indirect* effects distinction introduced earlier. To see the insights that this can provide, note the role of income in explaining the observed pattern of robberies. Income is negatively directly and indirectly associated with robberies. This means that the lower the income in an area, the more robberies take place in that area, and in neighbouring areas. This lends direct support to the argument that poverty is associated with crime, and that poverty induces crime spillovers. The same relationship is found

[5] The first crime type is an aggregation of the other 6 categories of theft crime considered here.

[6] Our posterior model probability calculations did not support the SEM model for any crime type, and chose the heteroskedastic model in each case.

for the ‘housing in poor condition’ variable for robberies.

In the case of ‘thefts from the person’ however, the relationship with houses in poor condition is more complex. Here we find that the more houses in poor condition there are in an area, the more thefts from the person in that area, but the fewer in surrounding areas. We think that what we are starting to get at with this particular result is some of the richness of explanations for the observed patterns of crime. In this case, those who venture out of their neighbourhoods to rob people are perhaps more experienced, older criminals who are more likely to use violence while robbing people, as compared to younger less mobile, less experienced criminals who seek to do the same thing in their own area, just with less violence. This is pure conjecture, but by examining the direct and indirect effects in this way we get a more complete picture of the complex spatial relationship underpinning observed patterns of crime.

A final aspect of the results that we consider here is the role of houses in poor condition in explaining the observed pattern of burglary of dwellings and non–dwellings. Houses in poor condition in an area is directly and positively associated with burglary of dwellings and non–dwellings in that area. This is not a surprise–the worse condition that houses are in the less secure they are likely to be, and the less secure that non-dwellings are also likely to be.

5 Conclusions

The main conclusions of this study is that the level of personal indebtedness does matter in explaining the observed pattern of robberies and thefts from the person. In addition, we have demonstrated the importance of accounting for spatial autocorrelation in modelling crime data. Further, we have shown how the calculation of the *direct* and *indirect* effects in spatial crime models can provide important insights into the complex relationship underpinning crime data. Future work will explore the dynamic nature of these relationships using data for a subsequent year–the only other year for which personal indebtedness data are available, as well as considering additional areas within England, UK.

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Table 1: Model results

Direct Effects

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

Indirect Effects

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

Total Effects

Variable	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%	Lower 95%	Mean	Upper 95%
Total value of CCJ	-0.029645	0.072679	0.176041	0.0185	0.116978*	0.222306	0.032473	0.075265*	0.119657	-0.014592	0.131687	0.284613	-0.032393	0.069622	0.173414	-0.015347	0.131921	0.292484	-0.218271	-0.017683	0.188776
Population turnover	-0.166735	-0.062027	0.044188	-0.318855	-0.206126*	-0.101496	-0.048145	-0.006335	0.037132	-0.210776	-0.051358	0.103303	0.015022	0.120021*	0.236338	-0.012825	0.148731	0.312239	-0.21991	0.006022	0.225781
% pop 0-15	-0.188514	-0.081606	0.025931	-0.303853	-0.195893*	-0.092583	-0.075931	-0.031845	0.009959	-0.561922	-0.376433*	-0.212301	-0.091	0.019886	0.132119	-0.176892	-0.016814	0.143858	-0.193935	0.031813	0.259488
% pop 16-24	-0.074489	0.020647	0.118294	-0.029426	0.071296	0.174289	0.00538	0.044881*	0.086997	-0.111673	0.034937	0.181625	-0.006125	0.097037	0.205734	-0.197001	-0.043518	0.105676	-0.130624	0.056792	0.254315
Houses in poor condition	0.025157	0.139894*	0.252945	0.332291	0.459641*	0.597431	-0.050719	-0.007225	0.036665	0.351657	0.530761*	0.737053	-0.089578	0.026457	0.142861	0.415704	0.605722*	0.812854	-0.149321	0.090497	0.330016
Income	-0.24287	-0.135025*	-0.031073	-0.400252	-0.284769*	-0.17424	-0.024698	0.014702	0.053437	-0.184738	-0.014312	0.154637	-0.128925	-0.024525	0.078867	-0.940366	-0.715742*	-0.519905	-0.19026	0.024393	0.240794
Pop. Density	0.020149	0.123712*	0.234847	-0.324185	-0.203357*	-0.092563	0.055735	0.098489*	0.140618	-0.303163	-0.119185	0.055888	-0.101712	0.005444	0.11316	-0.751249	-0.543264*	-0.355928	0.155619	0.382302*	0.626589

[a] A '*' next to the mean effect estimate indicates that the 95% credible interval does not contain zero indicating that the effect estimate is associated with the dependent variable.

Table 2: Variable details

All variables taken from http://www.neighbourhood.statistics.gov.uk/ operated by the UK Office of National Statistics (ONS).

Variable	Variable description
Value of CCJ	Total value of CCJ's granted in each area in 2004 in (£).
Population turnover	Net change in internal migration per 1,000 persons 2004/05.
% pop 0-15	Percentage of population aged 0-15 (mid-2004 model based estimates).
% pop 16-24	Percentage of population aged 16-24 (mid-2004 model based estimates).
Houses in poor condition	The modelled probability that a house in the area will fail to meet the UK Government 'Decent Homes' standard. Data used are averages of lower super output area values for 2004.
Income	Average weekly household total income (ONS model based estimate) 2004/05.
Pop. Density	Number of persons usually resident per hectare (based on 2001 census data).
All crime variables	Recorded crimes in 2004/05 per 1000 persons usually resident.