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Local Determinants of Crime:
Distinguishing Between Resident and Non-resident Offenders

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Nontechnical Summary

The use of local data has proved quite successful in providing empirical evidence on the determinants and causes of crime. However, depending on the definition of the administrative units, attempts to infer the role of the socio-economic background of offenders exclusively from the characteristics of the resident population at the location of crime may suffer from the presence of criminal mobility. Since, if the units of observation are small, a substantial amount of crime is often committed by non-resident offenders. This is a problem because the extent of offenses committed by non-resident offenders is likely related to the characteristics of the residential population at the location of crime. For instance, in an urban environment, residents with higher income and wealth may tend to segregate in suburban communities and leave inner-city areas for others. This tendency for spatial segregation raises intercommunity mobility of criminals if the propensity to commit crimes is inversely related to income and wealth and if offenders are attracted by the potential gains of criminal activities in the residential areas of the wealthy.

Given the possible importance of criminal mobility, this paper revisits the local determinants of crime distinguishing between resident and non-resident offenders. Whereas for the former the average individual characteristics as well as the socio-economic background are solely captured by variables referring to the location of crime, for non-resident offenders also spatial lags of residential population characteristics are employed. To take account of the correlation between crime rates of resident and non-resident offenders, equations for the two types of offenders are estimated jointly. In a dataset of cross-sections pooled over three years for some 430 or 500 municipalities depending on the type of crime considered, the estimation approach also takes into account spatial dependence across observations, as well as dependence across time. Moreover, due to a possible simultaneity bias with regard to the local property value the estimation relies on GMM estimation using several amenities as instruments.

Focusing on resident offenders, legal earnings opportunities and the expected gain from offenses are found to be important determinants of property crime, since the local property value as reflected in the local rent level, as well as income and unemployment all show the predicted effects. Several other characteristics of the municipalities shaping the environment within which crime is committed show reasonably expected effects. For instance, property crime is found to be positively related to the number of shops, the population size, and the number of daytime commuters. Also, other residential population characteristics such as the population share of juvenile males as well as the degree of family disruption do show the expected effects. Only the local share of foreign citizens – a heterogenous group generally characterized by immigrants with low skills – is not significantly related to crime committed by resident offenders. But, with regard to crime committed by non-resident

offenders the local share of foreign citizens shows a negative effect and the share of foreign citizens in the neighboring jurisdictions exerts a positive impact. This suggests that this variable is not only associated with the supply but also inversely associated with the demand for crime, *i.e.* it raises the number of potential offenders and reduces the number of attractive targets. Also the neighbors' income and unemployment are found to exert significant effects on crime committed by non-resident offenders.

With regard to property crime a comparison with a regression of the total crime rate on local characteristics highlights the importance of distinguishing between resident and non-resident offenders in presence of criminal mobility. In difference to the regression of the total crime rate, the system estimate confirms a positive significant impact of the socio-economic background of offenders in terms of poverty and inequality on crime committed by resident offenders. This difference is interesting in the light of Kelly (2000), who finds a strong positive effect of local inequality on violent crime but not on property crime for U.S. county data. The results presented in this paper corroborate his presumption that local data with small units of observation might confirm a positive association not only between inequality and violent crime but also between inequality and property crime. However, for both types of crime inequality only shows an effect on crime committed by resident offenders. This suggests that it is the joint presence of possible offenders and possible targets of crime within a municipality which drives the impact of local inequality on crime.

Local Determinants of Crime:
Distinguishing Between Resident and Non-resident Offenders*

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Abstract: The paper revisits the local determinants of crime using a spatial model distinguishing between resident and non-resident offenders. Employing data for German municipalities, the model is estimated by means of a spatial GMM approach. Focusing on resident offenders legal earnings opportunities and the expected gain from offenses are found to be important determinants of crime. Also the socio-economic background in terms of unemployment, poverty, and inequality proves significant for both property and violent crime. Whereas local inequality only shows an effect on crime committed by resident offenders, crime committed by non-resident offenders is shown to be significantly related to the characteristics in adjacent municipalities such as unemployment and income.

JEL-Classification: K42, R19, J61, J19

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1 Introduction

The use of local data has proved quite successful in providing empirical evidence on the determinants and causes of crime. For instance, several studies use differences in the risk of being detected and arrested between possible locations of crime. Examples include studies of deterrence effects (*e.g.*, Levitt, 1997) and studies of the higher crime in cities (*e.g.*, Glaeser & Sacerdote, 1999). Several studies use local data also to infer the role of the socio-economic background of potential offenders, in particular of local labor market conditions (*e.g.*, Gould, Weinberg, & Mustard, 2002) and of inequality. The latter has been studied by Kelly (2000) employing data for U.S. counties and Demombynes and Özler (2002) exploring data for South African police stations.

However, depending on the definition of the administrative units, attempts to infer the role of the socio-economic background of offenders exclusively from the characteristics of the resident population at the location of crime may suffer from the presence of criminal mobility. Since, if the units of observation are small, a substantial amount of crime is often committed by non-resident offenders. This is a problem because the extent of offenses committed by non-resident offenders is likely related to the characteristics of the residential population at the location of crime. For instance, in an urban environment, residents with higher income and wealth may tend to segregate in suburban communities and leave inner-city areas for others. This tendency for spatial segregation raises intercommunity mobility of criminals if the propensity to commit crimes is inversely related to income and wealth and if offenders are attracted by the potential gains of criminal activities in the residential areas of the wealthy (*e.g.*, Katzman, 1981). As a consequence, an attempt to infer the determinants of crime from the characteristics of the resident population alone might yield systematically biased results.

This paper sheds light on this implication of criminal mobility and revisits the empirical determinants of crime using local data. It employs a rich dataset of municipalities in Germany, where criminal mobility is quite significant: with regard to property crime, on average every second offense is committed by a non-resident offender. As the dataset provides information about whether or not an offender has its residence in the same jurisdiction where the offense is reported, the analysis explicitly distinguishes resident from non-resident offenders. For resident offenders the place of crime coincides with the place of residence and, therefore, local population characteristics are used to capture the socio-economic background of offenders. With regard to non-resident offenders this is captured by residential population characteristics of geographically neighboring jurisdictions. Thus, rather than removing spatial dependence from the data as suggested by Getis (1995) the analysis explicitly uses the spatial structure to identify the determinants of crime.[1]

[1]In this respect the current paper is related to the literature on the role of social interaction, which

The empirical investigation involves joint estimation of crime committed by resident and non-resident offenders. Using a dataset of cross-sections pooled over three years for some 430 or 500 municipalities depending on the type of crime considered, the estimation approach takes account of spatial dependence across observations, as well as dependence over time. Moreover, due to a possible simultaneity bias with regard to the local property value the estimation relies on GMM estimation using several amenities as instruments.

In particular with regard to property crime, the results highlight the importance of distinguishing between resident and non-resident offenders in presence of criminal mobility. Whereas a regression neglecting the difference between resident and non-resident offenders fails to show an impact of the socio-economic background of offenders in terms of both poverty and inequality on crime, the system estimate confirms a significant impact. Thus, taking account of criminal mobility the results presented in this paper corroborate the presumption of Kelly (2000) that data at a small level of aggregation might confirm a positive association not only between inequality and violent crime but also between inequality and property crime. However, inequality only shows an effect on crime committed by resident offenders suggesting that it is the joint presence of possible offenders and possible targets of crime which drives the impact of local inequality on crime.

The paper is organized as follows. The following section puts forward the basic investigation approach. Section 3 provides a description of the dataset. Section 4 reports the results, Section 5 concludes with a summary.

2 Investigation Approach

Whereas crime is ultimately resulting from the individual choice to commit an offense, the analysis below employs data for municipalities. Thus, it uses the cross-sectional variation in crime rates and in characteristics of jurisdictions to infer the determinants of the individual choice. Two sets of determinants are distinguished: locational characteristics and residential population characteristics. The former include characteristics of the administrative units where crime is reported, such as the size in terms of population or the geographic situation. The latter refer to the characteristics of the resident population of municipalities as for instance in terms of their income or their employment status. Note that, since residential population characteristics capture characteristics of the individuals in the aggregate, they reflect both characteristics of supply and demand of crime. In other words, residential population characteristics include characteristics of potential offenders as well as of potential victims of crime.

tests for a positive effect of crime in the local neighborhood on the individual propensity to commit crimes (*e.g.*, Case & Katz, 1991, Glaeser, Sacerdote, & Scheinkman, 1996).

Denoting the vector of locational characteristics with $\mathbf{v}_i$ and the vector of residential population characteristics with $\mathbf{y}_i$ the empirical relationship between the crime rate and these characteristics could be specified as

$$c_i \;=\; \mathbf{v}_i'\boldsymbol{\gamma} \;+\; \mathbf{y}_i'\boldsymbol{\delta} \;\;+\; u_i, \tag{1}$$

where c_i denotes the number of offenses at municipality i per resident and u_i is a residual. This simple specification neglects criminal mobility. More specifically, it neglects the fact that a part of the offenses committed at a locality is carried out by residents from other jurisdictions, which might have characteristics different from $\mathbf{y}_i$. In order to explicitly introduce criminal mobility consider the case of two jurisdictions. In presence of criminal mobility, we can distinguish crime at i committed by resident ($c_{i,i}$) and non-resident offenders ($c_{i,j}$). As in equation (1) crime committed by resident offenders could be determined by locational characteristics as well as by characteristics of the resident population at i

$$c_{i,i} \;=\; \mathbf{x}_i'\boldsymbol{\gamma_1} \;+\; \mathbf{y}_i'\boldsymbol{\beta_1} \;+\; u_{1,i}, \tag{2}$$

whereas crime committed by non-resident offenders could also be determined by characteristics of the population at j

$$c_{i,j} \;=\; \mathbf{x}_i'\boldsymbol{\gamma_2} \;+\; \mathbf{y}_i'\boldsymbol{\beta_2} \;+\; \mathbf{y}_j'\boldsymbol{\delta_2} \;+\; u_{2,i}, \quad j \neq i. \tag{3}$$

The joint presence of residential population characteristics at i and j in this equation reflects the ambiguity of those characteristics in capturing determinants of supply and demand of crime. If the residential population characteristics would only reflect the determinants of the supply of crime, a simplified version could be used, where $\boldsymbol{\beta}_2 = 0$.

In difference to the study of Fabrikant (1979) the data available to this study do not report all possible combinations of places of residence j and places of crime i. It only allows us to distinguish offenders with residence in municipality i from other, *i.e.* non-resident, offenders. Therefore, assuming that criminal mobility implies spatial transaction cost on behalf of the offender, the number of offenses committed by non-residents is regressed also on a spatial lag of the residential population characteristics

$$c_{i,-i} \;=\; \mathbf{v}_i'\boldsymbol{\gamma_2} \quad + \mathbf{y}_i'\boldsymbol{\beta_2} \quad + \mathbf{y}_{-i}'\boldsymbol{\delta_2} \;+\; u_{2,i}, \qquad \text{where } \mathbf{y}_{-i} = \sum_j \mathsf{w}[i,j]\,\mathbf{y}_j. \tag{4}$$

$\mathsf{w}[i,j]$ is a spatial weight associated with jurisdiction j ($\mathsf{w}[i,i] = 0$) such that the population characteristics of non-resident offenders are captured by spatial averages across neighboring municipalities. Following the literature on spatial econometrics (*e.g.*, Anselin,

1988) the analysis below defines neighbors as jurisdictions located within a certain distance and relies on inverse distances between i and j as weights.

Of course, this framework matches actual offenses with the background of offenders. A possible extension is to model the full choice set of each offender and to include indicators of the characteristics at alternative locations of crime as well. Following the assumption of spatial transaction cost, then, also spatial lags of locational characteristics could be added as regressors. However, probably because of the use of aggregate data for municipalities and the rather crude approximation of the choice set using spatial lags, no significance was found as is shown below.

If we assume that the local characteristics $\mathbf{v}_i, \mathbf{y}_i, \mathbf{y}_{-i}$ are not correlated with the random component of crime committed by resident and non-resident offenders $(u_{1,i}, u_{2,i})$, least squares estimation of the two equations (2) and (4) will provide us with consistent parameter estimates, which directly reveal the empirical determinants of crime. As is further discussed below, this assumption is not warranted with respect to all variables. Hence, in order to overcome this simultaneity problem instrumental variables are used, more specifically, a General Method of Moment estimator is employed.

As the system of equations (2 and 4) explicitly relies on spatial lags of explanatory variables it is important to take account of possible spatial dependence in the errors. One option is to use a heteroskedasticity and spatial-dependence consistent covariance matrix following Conley (1999). But, in presence of correlation between the residuals of the equations (2) and (4), joint estimation yields more efficient estimates.[2] In fact, as we will argue below such a correlation will simply result from the way the data are generated. Furthermore, due to the pooling of data for different years aside of a dependence across equations and a spatial dependence across units of observation, there might also be residual dependence across time periods. To control for common shocks across municipalities the pooled regression includes time specific effects in each equation, formally

$$
\begin{aligned}
c_{i,i,t} &= \mathbf{v}'_{i,t}\boldsymbol{\gamma}_1 + \mathbf{y}'_{i,t}\boldsymbol{\beta}_1 && + \alpha_{1,t} + u_{1,i,t}, && (5)\\
c_{i,-i,t} &= \mathbf{v}'_{i,t}\boldsymbol{\gamma}_2 + \mathbf{y}'_{i,t}\boldsymbol{\beta}_2 + \mathbf{y}'_{-i,t}\boldsymbol{\delta}_2 && + \alpha_{2,t} + u_{2,i,t}. && (6)
\end{aligned}
$$

Similar to Driscoll and Kraay (1998) additional dependence of residuals across time is taken into account by combining the spatial dependence consistent estimate of the covariance matrix following Conley (1999) with the autocorrelation consistent estimate suggested by

[2] The variance covariance matrix of the system is defined by

$$
\mathbf{S} = \begin{bmatrix} \mathbf{S}_{1,1} & \mathbf{S}_{1,2} \\ \mathbf{S}_{2,1} & \mathbf{S}_{2,2} \end{bmatrix}, \quad k,l = 1,2.
$$

where $\mathbf{S}_{k,l}$ is the covariance matrix of orthogonality conditions of equations k and l.

Newey and West (1987).[3]

Whereas the proposed system of equations (5) and (6) heavily draws on the separate information about resident and non-resident offenders, this distinction is not common in the empirical literature, which mainly deals with the overall crime rate. To facilitate comparisons the analysis below also presents results from a more standard regression of the crime rate on local characteristics

$$c_{i,t} \; = \; \mathbf{v}'_{i,t}\boldsymbol{\gamma} \; + \; \mathbf{y}'_{i,t}\boldsymbol{\beta} \; + \; \alpha_t \; + \; u_{i,t}, \tag{7}$$

where no spatial lag of residential population characteristics is taken into account.

3 Data

The dataset distinguishes suspects of crime with respect to resident offenders and non-resident offenders, the latter classified into offenders with residence elsewhere in the state, outside of the state or without registered residence. With regard to non-resident offenders, the analysis below focuses on suspects residing elsewhere in the state since only for municipalities within the state data on covariates are available. Since characteristics of offenders are only known if the police has found a suspect, i.e. if the police has cleared-up an offense, residence-specific crime rates are not directly available. But, similar to Levitt (1998) who analyzes age-specific crime rates, the number of offenses committed by resident

[3] The estimate of the four terms of the covariance matrix according to Footnote 2 is given by

$$\mathbf{S}_{k,l} = \sum_{m=0}^{p} \left(1 - \frac{m}{p+1}\right) \mathbf{S}_{k,l,m}, \quad k,l = 1,2, \; k \neq l,$$

where p is the maximum lag length and

$$\mathbf{S}_{k,l,m} = (1/NT) \sum_t \sum_i \sum_j 0.5K(i,j) \left[\mathbf{z}_{i,t}\hat{u}_{k,i,t}\hat{u}_{l,j,t-m}\mathbf{z}'_{j,t-m} + \mathbf{z}_{j,t-m}\hat{u}_{l,j,t-m}\hat{u}_{k,i,t}\mathbf{z}'_{i,t}\right],$$

where N is the number of observations, T is the number of periods, $\hat{u}_{k,i,t}$ is the first-step estimate of the residual of equation k, and $\mathbf{z}_{i,t}$ is the vector of instruments. Following Conley (1999) $K(i,j)$ is a two dimensional Bartlett kernel defined over a regular lattice field with a distinct address for each of the N jurisdictions. For $K(i,j) = 0$ if $j \neq i$ the covariance matrix is the system analogue of Newey and West (1987). Conversely, for $p = 0$ the covariance matrix is the system analogue of Conley (1999). The computation is programmed in TSP and has been crosschecked with a STATA routine provided by T. G. Conley.

and non-resident offenders is approximated using residence-specific shares of suspects

$$
\begin{aligned}
c_{i,i,t} &= \frac{S_{i,i,t}}{S_{i,t}} \times c_{i,t}, \\
c_{i,-i,t} &= \frac{S_{i,-i,t}}{S_{i,t}} \times c_{i,t},
\end{aligned}
$$

where $S_{i,i,t}$ and $S_{i,-i,t}$ indicate the number of resident and non-resident suspects for offenses committed at i, respectively, and $S_{i,t}$ is the total number of suspects. This approximation can be criticized for two reasons. First, knowing a suspect does not necessarily mean that he or she is really the offender because the suspicion might be wrong. But, as long as the probability of wrong suspicions does not differ between the groups of resident and non-resident suspects the estimation results will not be affected. Second, and likely more important, the probability of detection may differ with respect to the offender's place of residence. On the one hand, there are reasons to expect that resident offenders have a higher risk of detection as compared to non-resident offenders since it is more likely that a resident offender is known to a victim or witness. On the other hand, there is also an argument in favor of a smaller risk of detection for resident offenders if they successfully transform their informational advantage into lower detection probabilities. However, even if these potential sources of approximation error have practical relevance, the slope coefficients in the estimation will remain unaffected as long as the measurement error in the dependent variable is uncorrelated with the explanatory variables.

Nevertheless, there is a further implication of the above approximation: since the number of cases where the police has found a suspect is a random variable it might well introduce some error correlation between the equations for resident and non-resident offenders. For instance, if for some reason the total number of offenses increases but the police fails to find any suspects both the number of offenses committed by resident as well as by non-resident offenders will show an increase. Thus, variations in the number of cases not cleared-up by the police give rise to a correlation of shocks in the two equations which, however, is taken into account by the system estimator described above.

The investigation focuses on two broad categories of crime: property crime and violent crime. This distinction not only highlights the corresponding differences in the motivation of offenders, but also differences in the extent of crime spillovers (see below). The basic dataset reports offenses related to these two categories for all 1111 municipalities of a major German state (Baden-Wuerttemberg) at three different years (1989, 1992, 1995). As further depicted in the appendix there are many small jurisdictions: in 1995 as much as 612 municipalities have less than 5,000 residents. The presence of small jurisdictions in the dataset creates problems because the number of offenses reported at those municipalities is rather low and, as a consequence, small changes in absolute numbers lead

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max
Property crime (per 1,000 residents)				
Total crime rate	20.3	12.7	1.73	90.5
Crime rate related to resident offenders	9.63	7.12	0	50.1
Crime rate related to non-resident offenders†	8.61	6.00	0	64.0
Violent crime (per 1,000 residents)				
Total crime rate	.922	.588	.081	4.23
Crime rate related to resident offenders	.545	.428	0	3.36
Crime rate related to non-resident offenders†	.319	.259	0	1.74
Locational characteristics				
Monthly rent	9.15	1.36	5.61	12.7
Shops	4.41	1.44	.959	10.6
Discotheques	.041	.070	0	.432
Daily commuters	.151	.097	.021	.837
Population (log)	9.30	.747	8.33	13.3
Independent city	.018	.133	0	1
Border Rhineland-Palatinate	.024	.153	0	1
Border Hessia	.016	.126	0	1
Border Bavaria	.056	.230	0	1
Border Switzerland	.040	.196	0	1
Border France	.022	.147	0	1
Resident population characteristics				
Income	6.23	.734	4.25	13.9
Inequality	.426	.037	.352	.703
Poverty	1.57	1.12	0	10.2
Unemployment	3.84	1.20	1.69	9.53
Juvenile males	6.73	1.05	4.14	15.4
Divorce	5.32	1.70	1.50	11.7
Foreign citizens	7.59	3.85	.727	20.1

The basic sample consist of 1497 observations (3 years, 499 municipalities with population of at least 5,000 in 1995). Income is reported in 10,000 German Mark in 1995 prices. Monthly rent in German Mark in 1995 prices. Figures on property (violent) crime refer to 496 (431) municipalities where at least one offense is reported and solved by the police in each of the included years (1989, 1992, 1995).

† Excluding non-resident offenders residing outside the state and offenders without a registered residence.

to excessive fluctuations in the residence specific crime rates. Since attempts to employ count-data methods failed to obtain robust results we focus on the crime committed at municipalities with at least 5,000 residents. This leaves us with 499 jurisdictions (1497 observations), where, however, about 95 % of all crime reported has taken place.[4] Despite of the truncation of the smaller municipalities there are still some cases where no single offense has been reported or no suspect is known to the police in one of the years considered, such that the above approximation of residence specific crime rates is not defined. After removal of corresponding observations the sample consists of 496 municipalities in the case of property crime, and 431 municipalities in the case of violent crime. In each case the sample is balanced, *i.e.* there are observations on all three years (1989, 1992, 1995).[5] Descriptive statistics for the resulting crime rates for resident and non-resident offenders as well as for the total crime rate are displayed in Table 1. Note that, due to the exlusion of suspects with residence outside of the state or without registered residence, the rates of resident and non-resident offenders do not sum-up to the total crime rate. At the mean the property crime rate related to resident offenders is about half of the total crime rate, indicating that about every second offense is committed by non-resident offenders. In the case of violent crime with a figure of 40 % the share of offenses related to non-resident offenders is smaller.

Table 1 also provides a list of explanatory variables and shows corresponding descriptive statistics. The choice of the variables is basically motivated by the economic theory of crime (Becker, 1968, Ehrlich, 1973, 1996) which understands illegal activity as the result of an individual's decision comparing the costs and gains from a criminal act. Within this framework the gain is the expected illegitimate payoff from the considered offense and the costs comprise direct costs incurred, the foregone wages from legal income activity, and the expected penalty. The choice of explanatory variables is also in line with other "ecological theories" of crime such as *social disorganization theory* (Shaw & McKay, 1942, Sampson & Groves, 1989), *strain theory* (Merton, 1938), and *routine activity theory* (Cohen & Felson, 1979).[6] According to social disorganization theory five structural factors - low economic status, ethnic heterogeneity, residential mobility, family disruption and urbanization - lead

[4]In 1995 municipalities with at least 5,000 residents report 94,8 (94,3) % of all property crime (violent crime).

[5]Note that there are still some zero observations if all offenses in one year have been committed exclusively by resident or non-resident offenders, respectively. In the case of property crime committed by resident offenders this applies to about 1 % (18 cases) in the three years of observations, for non-resident offenders the figure is even smaller (11 cases). For violent crime the number of zero observations is higher (80 and 175 cases, for resident and non-resident offenders respectively). However, as already mentioned above due to lower robustness the analysis does not apply count-data methods.

[6]Entorf and Spengler (2002) present further sociological crime theories and discuss their empirical relevance.

to disorganization of community social organizations, which tends to reduce social control and, thereby, encourages crime (Sampson, 1997). According to strain theory individuals are motivated to commit delinquent acts because they have failed to achieve desired goals, such as economic success or social status. Finally, following routine activity theory a successful criminal violation involves three essential parts: an offender who is willing to commit a crime, a suitable target (person or property) to be victimized by the offender, and the absence of third parties (”guardians”) capable of preventing the violation (Cohen & Felson, 1979, p. 590). Hence, routine activities, as for instance activities which ”involve greater or lesser amounts of time spend within the confines of the immediate household” (Messner & Blau, 1987, p. 1037), are supposed to shape the chances for successful criminal offenses.

With regard to locational characteristics the analysis first of all considers a measure of the local property value. Since areas with a relatively high property value tend to comprise a higher value of tangible assets as well, they offer a higher expected gain from property related offenses, and, thereby, should exhibit a higher property crime rate. Because reliable figures on the market value of real estate are not available we use an average monthly apartment rent for a medium quality appartment as an indicator of the property value. However, numerous empirical studies show that property value and rent level are affected by the local crime rate among other local conditions (for an overview see Gyourko, Kahn, & Tracy, 1999). Regressing the crime rate on the local property value or the rent level would therefore introduce a simultaneity bias especially in the context of local municipalities where the cost of moving are small, relatively, and intercommunity mobility is high. To overcome this problem, the analysis relies on the well known capitalization of amenities into property values (*e.g.*, Gyourko et al., 1999) and employs several indicators of local amenities as instruments.[7]

Similar to the property value, the number of shops per 1,000 residents is also an indicator of illegal income opportunities as it represents the quantity of commercial targets. As shoplifting is an important component of theft we expect this variable to be strongly related to the occurrence of property crime. The number of discotheques per 1,000 inhabitants indicates locations where illegal income opportunities are higher due to crowding and noise. Moreover, this variable fits also with routine activity theory since drug or alcohol abuse may alter peoples behavior and attitudes toward crime (Roncek & Maier, 1991, p. 726). Population and commuting can be interpreted as indicators of urbanity and are

[7]The list of instruments includes the number of open air swimming pools, theaters, and tennis courts per capita. In addition, dummy variables capture the presence of a golf course, water sport opportunities, an equitation area, a sanatorium, and the classification of a municipality as a health resort, a recreation locality, or a climatic spa. Further variables measure the emission of industrial dust, as well as the share of nature and rural conservation areas.

expected to be positively related to crime, in particular, because probabilities of detection are lower in cities (Glaeser & Sacerdote, 1999). The commuting variable also fits with routine activity theory, since commuters are targets of crime as they spend time outside of their safe homes. Moreover, commuting is to some extent associated with using public transportation and thus brings together social groups with differing offending rates who usually are segregated (Tremblay & Tremblay, 1998, p. 295).

Several dummy variables capture jurisdictions directly situated at interstate or international borders. These variables are included since municipalities situated at the state's border might show systematic differences in comparison with non-border municipalities with respect to the distribution of the origin of offenders. Another dummy variable indicates independent cities (Kreisfreie Staedte) which are not associated to a specific county. These are units which comprise core cities and surrounding suburbs, and, therefore, will tend to show a lower number of non-resident offenders.

Note that the list of locational characteristics does not include a measure of law enforcement by the police. But, since the German constitution assigns police exclusively to the state level, local authorities do not decide on the number and equipment of police officers being on duty in their community. With police being administered at the state level, no detailed information is publicly available about how police forces are located among the 1111 municipalities. Basically, the size and distribution of police stations follows a strong central-place hierarchy and, therefore, varies strongly with population size. Thus, a part of the variation will be picked-up by the population size and commuting variables.

With regard to residential population characteristics the legal income opportunities of residents are captured by the income level and also by unemployment and poverty rates, which are inversely related to the legal income opportunities. Note that these variables could also be motivated by the strain theory as well as by social disorganization theory insofar as unemployment, low income, and poverty indicate lack of success and low economic status.

Following the literature on inequality and crime (*e.g.*, Kelly, 2000) a local measure of income inequality within jurisdictions is included.[8] From the economic theory of crime a larger spread between low and high incomes might indicate a higher gain from committing crime. However, as noted by Kelly (2000) disparity in incomes will also raise crime according to the strain theory and the social disorganization theory. Following the

[8]The local inequality measure is derived from the income tax statistics (see appendix). According to Lang, Noehrbass, and Stahl (1997) there is higher tax evasion at the upper parts of the income distribution. As a consequence the degree of inequality is underestimated. However, this is not crucial in the current analysis which does not focus on the level of inequality but on its difference across municipalities.

strain theory the failure of low income households to achieve a desired standard of living might be particularly depressing in the presence of high income households. At the same time, high inequality could also be correlated with the disorganization of community social organizations reducing the informal deterrence of crime.

Moreover, the share of residents with foreign citizenship is included. Albeit a heterogenous group, it is generally characterized by immigrants with low skills, which are not well integrated in the local municipalities. The population share of males aged 15 to 24 is added since the propensity for crime among juvenile males is known to be particularly high. As an indicator of family disruption the analysis employs the number of residents with a broken marriage relative to the sum of married and divorced residents.

4 Results

The results for property crime are presented in Table 2. The first two columns report results from a joint estimation of the system of equation (5) and (6).[9] Whereas the equation for resident offenders contains only local characteristics the equation for non-resident offenders includes also residential population characteristics of neighboring jurisdictions, *i.e.* spatial lags. As discussed above the regressions use several local amenity variables as instruments for the monthly rent level. According to the J-statistic of the overidentifying restrictions there is no indication of a specification problem. This confirms the choice of instrumental variables and, at the same time, the exclusion of resident population characteristics at neighboring municipalities from equation (5), since the estimation of both equations makes use of the full set of instruments.

The results for locational characteristics largely confirm the theoretical expectations. The monthly rent level shows a significant positive effect on crime committed by resident as well as by non-resident offenders. This suggests that the rent level and thus the property value is positively related with the demand for crime. However, in so far as the population structure differs with the rent level of a municipality, one might argue that also the supply of crime could vary (inversely) with the rent level. For non-resident offenders this would imply that the monthly rent level at neighboring jurisdictions should be included as a regressor. But, the additional inclusion of a spatial lag of the monthly rent level, instrumented with spatial lags of the amenities did not yield any significance.[10]

[9]Even though the system estimate is preferred the difference to the results from single estimation (available upon request) is rather small.

[10]The corresponding test of a restriction of an extended model based on the difference in the J-statistic yields a χ^2 of .037 at 1 degrees of freedom with P-value .847.

Table 2: Local Determinants of Property Crime

Dep. variable	Resid. off.			Non-resid. off.			Total crime		
Equation	(5)			(6)			(7)		
Locational characteristics at the location of crime									
Monthly rent	.726	(.204)	**	.993	(.530)	*	2.34	(.741)	*
Shops	.683	(.095)	**	.855	(.108)	**	1.61	(.218)	**
Discotheques	-.940	(1.46)		9.16	(2.56)	**	6.93	(3.75)	*
Daily commuters	4.27	(1.21)	**	16.9	(3.20)	**	24.7	(4.60)	**
Population (log)	3.61	(.239)	**	.613	(.284)	**	4.11	(.449)	**
Independent city	2.69	(1.04)	**	-4.96	(.806)	**	.507	(2.11)	
Border Rhineland-P.	2.12	(.691)	**	2.50	(1.53)		8.98	(2.58)	**
Border Hessia	2.04	(1.23)	*	-4.06	(.900)	**	2.10	(2.17)	
Border Bavaria	.748	(.441)	*	-.106	(.526)		1.76	(.826)	**
Border Switz.	1.38	(.549)	**	-.599	(.725)		1.54	(.975)	
Border France	4.18	(.971)	**	1.57	(.631)	**	10.5	(1.74)	**
Resident population characteristics at the location of crime									
Income	-1.47	(.353)	**	.005	(.343)		-1.77	(.781)	*
Inequality	11.8	(5.18)	**	-1.94	(5.97)		15.5	(10.5)	
Poverty	44.7	(12.5)	**	8.16	(14.7)		32.1	(30.5)	
Unemployment	108.	(14.0)	**	6.34	(15.5)		200.	(34.4)	**
Juvenile males	87.5	(22.2)	**	15.9	(20.3)		93.6	(44.8)	**
Divorce	49.0	(14.9)	**	59.6	(24.0)	**	112.	(45.6)	**
Foreign citizens	5.86	(3.73)		-17.4	(4.91)	**	-16.8	(9.00)	
Resident population characteristics at neighboring municipalities									
Income				-.342	(.112)	**			
Inequality				-19.1	(15.0)				
Poverty				28.3	(17.6)				
Unemployment				49.9	(11.7)	**			
Juvenile males				2.09	(10.8)				
Divorce				5.74	(43.9)				
Foreign citizens				7.98	(3.40)	**			
Mean of dep.var.	9.63			8.61			20.3		
Nobs	1488						1488		
J-Statistic(dof.)	34.2(31)						21.1(12)		

GMM estimates (standard errors in parentheses), where the set of instruments excludes the monthly rent level and includes 13 variables capturing local amenities. With regard to resident and non-resident offenders the results are obtained from joint system estimation. Results for the total crime rate are obtained from single equation estimation. Coefficients are marked with one or two stars, depending on whether the significance level is 0.1 or 0.05 respectively. All estimations take account of time specific effects.

Aside of the rent level also other locational characteristics tend to raise crime. The number of shops is associated with an increase in crime irrespective of the residence of the offender. Discotheques show significant positive effects on crime committed by non-resident offenders. Population size as well as commuting show positive effects on crime committed by both resident and non-resident offenders, which supports the view of cities offering a crime prone environment. As in the case of the monthly rent level one might wonder whether the population size of neighboring jurisdictions is also correlated with the supply of non-resident offenders. But, the additional inclusion of a spatial lag of population size is rejected by formal testing.[11] Consistent with the partial isolation of independent cities from the neighborhood the independent city dummy shows different effects on crime committed by resident and non-resident offenders. For the same reason, the differences found for the border dummies seem reasonable.

With the exception of the share of residents with foreign citizenship in the equation for resident offenders all residential population characteristics at the location of crime prove significant and show the expected sign. Also the local Gini coefficient proves significant. In the equation for non-resident offenders the significance of the spatial lags for income and unemployment indicate that improved legal income opportunities of the population in neighboring jurisdictions are associated with a reduction of crime spillovers. Remarkably, also the share of residents with foreign citizenship shows a positive significance at the neighboring municipalities and a negative sign at the location of crime. This indicates that a high share of foreign citizens reduces inward spillovers and raises outward spillovers of crime. A possible explanation is that this variable is related positively to the supply of crime and at the same time negatively to the demand of crime. Interestingly, the measure of family disruption shows a positive significance at the location of crime. This could possibly indicate that locations with a high degree of family disruption exhibit lower social control as suggested by the social disorganization theory.

For means of comparison, the third column of Table 2 provides results for a more standard regression of the overall crime rate. It shows results from the corresponding single equation GMM estimation, as above, based on the amenity variables as instruments for the monthly rent level. Whereas the results show a lot of similarity, it is interesting to note that with regard to inequality, poverty, and the share of foreign citizens no significant effects are found. As these variables show significance in the system estimate distinguishing between resident and non-resident offenders this failure is consistent with the view that an attempt to infer the characteristics of the socio-economic background of offenders from local characteristics alone might yield biased results.

[11] The corresponding χ^2 statistic shows a value of .014 at 1 degree of freedom and a P-value of .970. Also a joint test for the presence of spatial lags of population and rent level did not yield a significance (the χ^2 statistic shows a value of .616 at 2 degrees of freedom and a P-value of .735).

Table 3: Local Determinants of Violent Crime

Dep. variable	Resident off.			Non-resident off.			Total crime		
Equation	(5)			(6)			(7)		
Locational characteristics at the location of crime									
Monthly rent	-.044	(.018)	⋆⋆	-.031	(.027)		-.019	(.043)	
Shops	.008	(.008)		.010	(.007)		.019	(.015)	
Discotheques	-.057	(.132)		.186	(.122)		.232	(.241)	
Daily commuters	-.068	(.111)		.292	(.075)	⋆⋆	.326	(.165)	⋆⋆
Population (log)	.124	(.018)	⋆⋆	-.001	(.015)		.122	(.032)	⋆⋆
Independent city	.292	(.081)	⋆⋆	-.078	(.037)	⋆⋆	.344	(.105)	⋆⋆
Border Rhineland-P.	.229	(.099)	⋆⋆	.030	(.047)		.334	(.147)	⋆⋆
Border Hessia	.438	(.095)	⋆⋆	-.121	(.039)	⋆⋆	.441	(.154)	⋆⋆
Border Bavaria	.044	(.037)		-.021	(.032)		.045	(.058)	
Border Switz.	.072	(.045)		.044	(.035)		.143	(.077)	⋆
Border France	.192	(.064)	⋆⋆	.165	(.039)	⋆⋆	.452	(.090)	⋆⋆
Resident population characteristics at the location of crime									
Income	-.041	(.026)		-.013	(.020)		-.077	(.048)	
Inequality	1.31	(.419)	⋆⋆	.331	(.344)		1.68	(.724)	⋆⋆
Poverty	4.79	(1.22)	⋆⋆	.392	(.811)		3.83	(1.84)	⋆⋆
Unemployment	5.96	(.973)	⋆⋆	-.407	(.945)		8.76	(2.00)	⋆⋆
Juvenile males	1.18	(1.28)		4.73	(1.61)	⋆⋆	6.10	(2.52)	⋆⋆
Divorce	3.08	(1.19)	⋆⋆	4.02	(1.20)	⋆⋆	4.45	(2.74)	⋆⋆
Foreign citizens	1.80	(.286)	⋆⋆	-.071	(.282)		1.53	(.509)	⋆⋆
Resident population characteristics at neighboring municipalities									
Income				-.018	(.007)	⋆⋆			
Inequality				-1.09	(.826)				
Poverty				-1.38	(.816)	⋆			
Unemployment				1.46	(.560)	⋆⋆			
Juvenile males				1.44	(.603)	⋆⋆			
Divorce				3.04	(2.23)				
Foreign citizens				.329	(.197)	⋆			
Mean of dep.var.	.545			.319			.922		
Nobs	1293						1293		
J-Test(dof.)	16.3(31)						13.4(12)		

GMM estimates (standard errors in parentheses), where the set of instruments excludes the monthly rent level and includes 13 variables capturing local amenities. With regard to resident and non-resident offenders the results are obtained from joint system estimation. Results for the total crime rate are obtained from single equation estimation. Coefficients are marked with one or two stars, depending on whether the significance level is 0.1 or 0.05 respectively. All estimations take account of time specific effects.

The estimation results for violent crime are presented in Table 3. Again the first two columns report results for the two equations of the system. With regard to locational characteristics there are several differences as compared to property crime. Shops and discotheques prove insignificant, and an effect of daily commuters is only found for non-resident offenders. This is, however, not really surprising if one takes into account that violent crime does not include offenses such as shoplifting and picketpocking. It is also interesting to note that with regard to the rent level, a negative effect is found, indicating that areas of high property value are associated with low violent crime. Again it has been tested in an extended model whether the monthly rent level at neighboring jurisdictions should be included, but no significance was found.[12]

With regard to the effects of resident population characteristics on crime committed by resident offenders a strong significance is found for most variables. As in the case of property crime, there is a significant positive effect of local inequality and poverty. Only income and, somewhat surprisingly, the population share of juvenile males are insignificant. But note that these variables are significantly associated with crime spillovers. At any rate, the results for the determinants of crime spillovers are somewhat more difficult to interprete than those for property crime. However, as criminal mobility is less important with violent crime and since violent crime is less strongly associated with economic incentives it is no surprise that the equation for violent crime committed by non-resident offenders is less clear-cut as compared to the case of property crime. Correspondingly, in difference to the case of property crime the standard regression of the violent crime rate on local characteristics does not show striking differences to the system estimate for resident-offenders.

5 Summary and Conclusions

Given the possible importance of criminal mobility, this paper has revisited the local determinants of crime distinguishing between resident and non-resident offenders. Whereas for the former the average individual characteristics as well as the socio-economic background are solely captured by variables referring to the location of crime, for non-resident offenders also spatial lags of residential population characteristics are employed. To take account of the correlation between crime rates of resident and non-resident offenders, equations for the two types of offenders have been estimated jointly. In a dataset of cross-sections pooled over three years for some 430 or 500 municipalities depending on the type of crime

[12] The χ^2 statistic shows a figure of 1.69 at 1 degree of freedom and a P-value of .193. The joint test on the rent level and the population size of neighboring jurisdictions has a χ^2 statistic of 3.59 at 2 degrees of freedom and a P-value of .166.

considered, the estimation approach also takes into account spatial dependence across observations, as well as dependence across time. Moreover, due to a possible simultaneity bias with regard to the local property value the estimation relies on GMM estimation using several amenities as instruments.

Focusing on resident offenders, legal earnings opportunities and the expected gain from offenses are found to be important determinants of property crime, since the local property value as reflected in the local rent level, as well as income and unemployment all show the predicted effects. Several other characteristics of the municipalities shaping the environment within which crime is committed show reasonably expected effects. For instance, property crime is found to be positively related to the number of shops, the population size, and the number of daytime commuters. Also, other residential population characteristics such as the population share of juvenile males as well as the degree of family disruption do show the expected effects. Only the local share of foreign citizens – a heterogenous group generally characterized by immigrants with low skills – is not significantly related to crime committed by resident offenders. But, with regard to crime committed by non-resident offenders the local share of foreign citizens shows a negative effect and the share of foreign citizens in the neighboring jurisdictions exerts a positive impact. This suggests that this variable is not only associated with the supply but also inversely associated with the demand for crime. Also the neighbors' income and unemployment are found to exert significant effects on crime committed by non-resident offenders.

With regard to violent crime the results show some differences. The property value no longer raises but tends to reduce the crime rate. Also locational characteristics such as the number of shops and the population size do not show significant effects. However, for resident offenders, most of the residential population characteristics still show the expected effects. With regard to non-resident offenders, the results confirm the significance of spatial lags of the residential population characteristics. As compared to the results for property crime the results for non-resident offenders are somewhat less clear-cut. To some extent this may reflect the lower extent of criminal mobility in the case of violent crime.

With regard to property crime a comparison with a regression of the total crime rate on local characteristics highlights the importance of distinguishing between resident and non-resident offenders in presence of criminal mobility. In difference to the regression of the total crime rate, the system estimate confirms a positive significant impact of the socio-economic background of offenders in terms of poverty and inequality on crime committed by resident offenders. This difference is interesting in the light of Kelly (2000), who finds a strong positive effect of local inequality on violent crime but not on property crime for U.S. county data. The results presented in this paper corroborate his presumption that local data with small units of observation might confirm a positive association not only between inequality and violent crime but also between inequality and property crime. However, for both types of crime inequality only shows an effect on crime committed by resident offenders. This suggests that it is the joint presence of possible offenders and possible targets of crime within a municipality which drives the impact of local inequality on crime.

Data Sources and Definitions

Municipalities: The basic dataset consists of the 1111 municipalities of the German state of Baden-Wuerttemberg (BW). BW covers a total area of 35,752 square kilometer (sqkm) (13,800 square miles (sqm)) with an average community area size of about only 32.2 sqkm (12.4 sqm). For comparison average US county size is about 1,127.5 sqm (own computations based on County and City Data Book, 1988). The average population density is 291 inhabitants per sqkm or 753.7 inhabitants per sqm. For comparison, average US population density is about 68.1 per sqm (cf. County and City Data Book, 1988).

Table 4: Local Population Distribution in the State of Baden-Wuerttemberg

Population range			Number	Pop. share	Cum. pop. share
	$<$	1,000	90	.005	.005
1,000	-	2,500	216	.040	.045
2,500	-	5,000	306	.108	.152
5,000	-	10,000	259	.172	.324
10,000	-	20,000	149	.193	.517
20,000	-	50,000	68	.202	.718
50,000	-	100,000	14	.090	.809
	$\geq$	100,000	9	.191	1.00
		Total	1111	1.00	

1995 population figures.

Crime data: The crime data is provided by the State Criminal Police Office (Landeskriminalamt) Baden-Wuerttemberg. The following definitions refer to the German penal code ("Strafgesetzbuch" (StGB)).

Property crime comprises theft (§242 StGB), home and family theft (§247 StGB), petty theft and embezzlement (§248a StGB), unauthorized use of a vehicle (§248b StGB), tapping of electrical power (§248c StGB), aggravated theft (§243 StGB), theft with weapons and gang theft (§244 StGB) and serious gang theft (§244a StGB).

Violent crime comprises murder (§211 StGB), manslaughter and killing on demand (§§212, 213, 216 StGB), killing of infants (§217 StGB), rape (§177 StGB), robbery, extortion by means of force and predatory attack of motorists (§§249-252, 255, 316a StGB), fatal assault (§§226, 227, 229(2) StGB), aggravated assault, serious assault and poisoning (§§223a, 224, 225, 227, 229 StGB), kidnapping (§239a StGB), taking of hostages (§239b StGB) and attack on air traffic (§316c StGB).

Mean income and inequality (Gini Coefficient) are calculated from the income tax statistics which report gross income (the income for married couples is split). Income is reported in 8 income classes ([1, 10000]; [10000, 20000]; [20000, 30000]; [30000, 40000]; [40000, 50000]; [50000, 75000]; [75000, 100000]; [100000 or more], all in DM). Fore each class the number of taxpayers as well as the mean income are reported. Whereas the calculation of the overall mean income is straightforward, that of inequality is more difficult, since little is known about the income distribution within each class. However, as pointed out by Cowell (1995), knowing the mean income and the number of occupants of each class upper and lower limits for a variety of inequality measures can be found. Lower limits are found by assuming that everyone in class i receives exactly the same income, namely, the average income (μ_i) in that class. Upper limits result from the assumption that there is maximum inequality within each class. This implies that the members of class i receive either the lower limit income (a_i) or the upper limit income (a_{i+1}) but no intermediate incomes. The share of those class members who are assumed to stick at the lower limit of class i is given by $\lambda_i = \frac{a_{i+1}-\mu_i}{a_{i+1}-a_i}$.[13] One may now write the lower (G_L) and upper limit (G_U) of the Gini Coefficient as

$$G_L = \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \frac{n_i n_j}{n^2 \bar{y}} \left| \mu_i - \mu_j \right|,$$

$$G_U = G_L + \sum_{i=1}^{k} \frac{n_i^2}{n^2 \bar{y}} \lambda_i \left[\mu_i - a_i \right],$$

where j is an additional group index, k indicates the number of classes, n_i (n_j) is the number of taxpayers within group i (j), n is the absolute number of taxpayers across all groups and $\bar{y}$ is the mean income across all groups. As usual in grouped income data the highest class is reported without an upper limit (*e.g.*, 100.000 DM or more). This open class however is not a problem. Although a_{k+1} is required for the calculation of G_U, the measure proved insensitive to alternative specification of the upper bound. In the present study the limit is set to 1 Million DM. As G_L and

[13]This formula ensures that the assumed average income within the class tallies with the observed number μ_i.

G_U determine the limits of the Gini coefficient it is evident that the true measure lies somewhere in between. For the Gini coefficient we use a compromise value suggested by Cowell (1995) by taking $\frac{2}{3}$ of its lower bound and adding to it $\frac{1}{3}$ of its upper bound, which "[...]works extremely well for most distributions" (Cowell, 1995, p. 116).

Further covariates are obtained from the State's Statistical Office (Statistisches Landesamt) Baden-Wuerttemberg. For several covariates data are only available for one of the considered years. Instead of performing the estimations without these variables and since the analysis deals with the cross-sectional distribution anyway, the corresponding figures are assigned to all years. This refers to the monthly rent level referring to apartments equipped with bath and kitchen taken from the last German population census 1987. Publicly supported housing is excluded. Even though the cross-sectional distribution is constant the data for 1989, 1992, and 1995 are adjusted with the state rent price index. The number of welfare recipients at the level of municipalities is only available for 1995. Commuting, unemployment, divorce and residents with foreign citizenship are only available for 1987 - the year of the last German population census. The number of shops and discotheques is taken from the establishment census, 1993.

Amenities used as instrumental variables for the rent level have also been obtained from the State's Statistical Office. The list of amenity variables includes the number of open air swimming pools, tennis courts per capita, the presence of a golf course, of water sport opportunities, and of an equitation area all referring to July 1989. Moreover, the touristic classification of municipalities (taken from the German Automobile Association) indicating a health resort, a recreation locality, or a climatic spa as of 1987 is employed. Furthermore, a dummy variable captures the presence of a sanatorium in 1988. Also the number of theaters per capita in 1987 is used. Two variables indicate the share of natural resort and land reservation areas in the county or independent city. Finally the amount of industrial dust per county (or independent city) area as an average of the figures in 1985 and 1990 is employed.

Spatial weighting matrix: Euclidian distances are computed from a digital map of the geographical position of the administrative center of each community. The employed matrix defines local neighbors as communities located within a distance of 30 kilometers (km). This results from using commuting of the working population as an indicator of the geographic proximity, as 90 % of the male commuters – as a proxy for full-time employed commuters – have a commuting distance up to 30 km (18,65 miles). This figure was obtained by means of linear interpolation based on relative frequencies of commuting distances published by Heidenreich (1988). Each neighboring community is weighted according to the inverse of its relative distance. Note that due to a better empirical performance, row-standardization is not imposed.

This implies, that the total strength of effects exerted by neighboring municipalities is not restricted to be the same across municipalities. If a municipality is located in large distance to others it will thus tend to be less affected by its neighbors.

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