Metropolitan fragmentation, law enforcement effort and urban crime

William C. Wheaton

Department of Economics, Center for Real Estate, MIT, Cambridge, MA 02139, USA

Received 1 June 2005; revised 26 January 2006
Available online 20 March 2006

Abstract

This paper investigates how a system of local law enforcement agencies operates within a metropolitan area. In a cross section of 236 US MSA the paper finds that greater agency fragmentation leads to less law enforcement effort (resources), but also to less crime! This seemingly contradictory result is robust to many alternative specifications. To explain the result a model is developed in which a unilateral increase in local law enforcement effort has the effect of “spatially displacing” criminals as well as incarcerating them. In this model, greater agency fragmentation by itself leads to lower spending but higher crime. The model is expanded to include an “X-efficiency” advantage by smaller agencies, which is shown to be necessary to explain the empirical results. The exact source of this advantage however, is not uncovered.

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“We don’t [cooperate]. Law enforcement is the most turf-based institution in American. And when you have upwards of 19,000 separate police forces in a purposely decentralized law-enforcement environment, it’s a lot of individual turf to protect.”

(William Bratton, 2002 Interview in Commonwealth Magazine).

1. Introduction

Recently there has been renewed interest in how greater jurisdictional fragmentation within US metropolitan areas impacts the delivery of services and the distribution of tax burdens with “Tiebout” type competition. Rhode and Strumpf [13] argue that over the last century, increased municipal fragmentation has not led to wider disparities in government services. Consistent with
this, Epple and Sieg [3] and Davidoff [2] find surprisingly little income sorting—despite the increased opportunity for such that is afforded by extensive municipal fragmentation. Hoxby [7] contributes most recently to this literature by showing that the existence of many smaller school districts results in both lower average school expenditures per pupil as well as improved average school test performance across those districts. She infers that school district “competition” generates greater efficiency and this then reduces the need for public expenditure.

This paper extends this line of inquiry into the arena of local law enforcement. In the US, most law enforcement within metropolitan areas is conducted by town or municipal police departments. In addition, a small number of Country Sheriffs play a role particularly in unincorporated portions of an MSA. Of course State police and the FBI may also contribute broader law enforcement effort. How such a large number of local agencies cooperate and compete has been the subject of considerable discussion by the profession, but has not been well researched by economists.

Within the economics literature there have been two strands of research. The first deals with the causal relationships between aggregate criminal activity, sentencing and law enforcement (Levitt [9,10], Ehrlich [4]). The second is more recent and has begun to investigate the flow of criminal activity across jurisdictions and the behavior of towns in the presence of such criminal “mobility.” The recent papers by Helsley and Strange [6], Freeman–Grogger–Sonstelie [5] and Newlon [12] each begins to examine the “spatial displacement” of crime and how this impacts enforcement effort (there is a parallel literature on “temporal displacement” as recently summarized in Jacob–Lefgren [8]).

There also has been an extensive more sociological literature about crime, deterrence and the effectiveness of various law enforcement strategies (e.g. Wilson and Petersilia [16], Sherman et al. [14]). This literature argues that “local knowledge,” “community policing” and other neighborhood level strategies are more important to controlling crime than increases in aggregate resources. Neighborhood level policing, however, also can create problems of coordination and loss of economies-to-scale.

This paper both unites and extends these various strands by developing a full Nash Equilibrium model of local law enforcement effort and criminal flows between local jurisdictions. Local agencies expend funds to increase arrests which in turn reduces local criminal activity. The effectiveness of arrests on reducing local crime is a central determinant of the expenditure decision and shifts the “arrest demand” schedule. In terms of local “criminal supply,” a total pool of regional criminals—that are not incarcerated—distributes itself across jurisdictions to achieve a common level of “utility.” Local arrest effort not only reduces the regional pool (through incarceration) but can also reduce the local share of this pool that is attracted to the town (spatial displacement). The model also incorporates a direct “scale” effect—allowing larger communities to be more or less “X-efficient” at controlling crime—per dollar of resources spent. This incorporates many of the issues discussed in the “community policing” literature and allows town size to shift the “criminal supply” schedule.

Within this framework, a fragmented metropolitan area containing many “smaller” jurisdictions exhibits two differences versus a less-fragmented area. First, fragmentation directly alters the “X-efficiency” of law enforcement effort and hence shifts the local criminal supply schedule that all towns face. Secondly, it also directly shifts the demand for law enforcement effort. This comes about as each town in a fragmented system has less incarceration impact on the regional pool, but at the same time greater “displacement” effect on the share of the pool operating in their jurisdiction. The net magnitude of these two effects determines whether a larger number of “smaller” jurisdictions face more or less incentive to expend effort. Overall, then MSA frag-
mentation can have a range of impacts on expenditure and crime depending on the magnitude of these various schedule shifts.

Empirically, the paper develops an extensive cross section data base for 236 MSAs in 1997—a year in which all local law enforcement agencies are surveyed. Included is data on MSA criminal activity, the number of agencies and their effort levels (wages and expenditure). Since the number of agencies has changed little between (5-year) surveys, the paper takes the view that fragmentation is largely “historic” and hence exogenous with respect to current criminal activity. Using a wide range of reduced form equations, it turns out that MSAs with a larger number of agencies clearly spend less in aggregate on law enforcement effort. Surprisingly, such MSAs also have less crime. These results withstand numerous empirical specifications.

These results are consistent with the model developed only under a particular set of assumptions. First, a necessary condition is that greater fragmentation increases law enforcement “X-efficiency.” Secondly, it must also be the case that any shifts in the demand schedule caused by fragmentation must be more modest in magnitude. Assigning instruments to both supply and demand equations reveals that indeed the reduced form result comes from the required shift to both schedules. These results are quite consistent with the type of argument presented by Hoxby [7] in which fragmentation somehow increases the efficiency of a public agency (in that case local schools) which then reduces the need (and demand) for resources.

The paper is organized as follows. Sections 2 through 4 develop the model and its predictions about the impact of metropolitan fragmentation on law enforcement effort and crime. Section 5 describes the data and then Section 6 presents a range of reduced form equations as well as an “assignment” of instruments to estimate a structural model. These results confirm the reduced form estimates. Section 7 concludes with some suggestions about how to interpret the empirical results.

2. Modeling the flow of criminal activity across Jurisdictions within MSAs

We begin with an MSA composed of $N$ communities (subscripted with $i$, $k$, or $j$) each of which generates arrests at the per capita rate $a_i$. Towns internally are composed of representative tax-paying agents who need not be the same across towns. Each town $i$ has $h_i$ such agents and so MSA population is $H = \sum h_i$.\(^1\) Aggregate MSA arrests are $\sum a_ih_i$.

The flow of crime per capita in each town is noted as $c_i$, and crime and criminals are assumed to be equal. Each available criminal commits one crime in one town. Thus the number of criminals operating in each town is $c_ih_i$ and the regional pool of criminals committing crimes (those not incarcerated) is $\sum c_ih_i$. This latter summation is equivalently equal to the aggregate MSA flow of crime.

The MSA has a total pool of potential criminals which is $C$ and we assume for simplicity that this pool is fixed (there is no inducement into or out of crime). Following Levitt [9] these criminals are either incarcerated or committing crimes. When arrested, criminals serve a common MSA level sentence length of $L$. In equilibrium, there is a steady state flow condition between releases from incarceration and arrests into incarceration—when aggregated across towns. This is expression (1) below. To account for “X-efficiency” a scale factor ($\alpha$) is introduced between arrests and the inflow into incarceration. If $\alpha > 1$ then an arrest made in a larger town will have a higher “effective” incarceration effect. If $\alpha < 1$ then smaller towns are more efficient, and if

\(^1\) We use the convention of having an un-subscripted summation $\sum$ in the text refer to the full set of towns. When used in separate equations, subscripts will indicate the summation range.
\[ \alpha = 1 \] an arrest has the same impact on criminal incarceration (one for one) regardless of town size.

\[
\left( C - \sum_{i=1}^{N} c_i h_i \right) / L = \sum_{i=1}^{N} c_i h_i^\alpha a_i
\]  

(1)
yields:

\[
C = \sum_{i=1}^{N} c_i h_i + \sum_{i=1}^{N} c_i h_i^\alpha a_i L.
\]

Following Helsley and Strange [6] we assume that the movement of criminals across towns is perfectly elastic with respect to the utility that they obtain from such activity. We use a more general criminal utility function \( V \), rather than expected criminal returns, and have it depend negatively on that town’s arrest rate as well as on criminal density \( c_i \). In trying to explain the existence of crime “hot spots,” Freeman–Grogger–Sonstelie [5], assume when there are more criminals concentrated in an area, the gains from criminal activity are diluted for each individual criminal.\(^2\) With perfect criminal mobility, criminal utility must be equal across towns:

\[
V(a_i, c_i) = V^*, \quad \text{over all } i = 1, N,
\]

(2)

\[
V'_{1i} = \partial V / \partial a_i \leq 0,
\]

\[
V'_{2i} = \partial V / \partial c_i \leq 0.
\]

Equation (1) when combined with the set of \( N \) equations (2) determines the spatial pattern of crime \( (c_i) \) and criminal utility level \( V^* \)—given the spatial pattern of arrests \( a_i \). The ratio \( V'_{1i} / V'_{2i} \) determines how many fewer criminals have to operate in a town as that town increases its arrest effort—to keep criminal utility fixed.

In order to better understand the properties of these flow equations, we examine the derivatives of the system as a whole—the impact of each town’s arrest rate on crime in both that jurisdiction as well as all others.

Totally differentiating (1) and (2) with respect to \( a_i \) we get the equations in (3):

\[
(h_i + a_i h_i^\alpha L) \frac{dc_i}{da_i} = -c_i h_i^\alpha L - \sum_{j \neq i} \frac{dc_j}{da_i} (h_j + a_j h_j^\alpha L)
\]

(3)

\[
V'_{1i} + V'_{2i} \frac{dc_i}{da_i} = \frac{dV^*}{da_i}
\]

or

\[
\frac{dc_i}{da_i} = \left( \frac{dV^*}{da_i} \right) / V'_{2i} = V'_{1i} / V'_{2i} \leq 0
\]

\[
V'_{2j} \frac{dc_j}{da_i} = \frac{dV^*}{da_i}
\]

\[
\frac{dc_j}{da_i} = \left( \frac{dV^*}{da_i} \right) / V'_{2j} \leq 0.
\]

Solving for \( dV^*/da_i \):

\[
\frac{dV^*}{da_i} \left[ N \sum_{k=1}^{N} \frac{h_k + a_k h_k^\alpha L}{V'_{2k}} \right] = -c_i h_i^\alpha L + (h_i + a_i h_i^\alpha L) \frac{V'_{1i}}{V'_{2i}}.
\]

(4)

\(^2\) Freeman–Grogger–Sonstelie also assumes that when criminals spatially concentrate they “mask” each other and can reduce the arrest probability for any one of them. In this paper arrests are taken as being exogenous and independent of criminal density.
On the left-hand side of (4), the summation term is negative and so dividing through reverses all signs on the right-hand side. On the right-hand side, the first term is negative and represents the “incarceration” effect. By reducing the total MSA pool of criminals on the street greater arrests in one town improve criminal utility since MSA wide criminal density is lower. The second term on the RHS is positive (hence its impact on \( V^* \) is negative) and it represents a “displacement” effect. By increasing arrests, one town “scare” criminals to all other towns. In those towns, where arrests are fixed, this displacement effect tends to increase criminal density and hence reduces \( V^* \).

If \( V_{1i}' / V_{2i}' \) is “large” (it is positively signed) then there is much “displacement” of criminals to other towns when town \( i \) expands arrest effort. This makes it likely that \( dV^*/da_i < 0 \) and this implies \( dc_k/da_i > 0 \). On the other hand if \( V_{1i}' / V_{2i}' \) is “small” then there is little “displacement” of criminals to other towns when town (i) expands effort, and in this case the incarceration effect dominates with \( dV^*/da_i > 0 \), and \( dc_k/da_i < 0 \).

Combining (3) and (4) we solve for the impact of town arrests on their own supply of criminals \( dc_i/da_i \) and get (5):

\[
\frac{dc_i}{da_i} V_{2i}' \sum_{k=1}^{N} \left[ \frac{h_k + a_k h_i^\alpha L}{V_{2k}'} \right] = -c_i h_i^\alpha L - \sum_{j \neq i} V_{1i}' \left[ \frac{h_j + a_j h_i^\alpha L}{V_{2j}'} \right].
\]

The left-hand side summation term is positive, and on the right-hand side, both terms are negative. Hence \( dc_i/da_i \) is always signed negative and the model produces a traditional “criminal supply” schedule for each town.

3. Town choice of resources to spend on arrests

The resident agents in each town all have homogeneous income \( y_i \) and hence aggregate metropolitan income is \( \sum y_i h_i \). With these resources agents in each town select an arrest rate, where arrests “cost” \( K \) dollars to achieve. With a resident utility function that depends on crime and “other” expenditure, residents maximize utility (6), which yields the first-order conditions (7)

\[
\text{Max} \quad \text{w.r.t.} : a_i : U(y_i - a_i K, c_i),
\]

\[
U_{1i}' = \frac{K}{dc_i/da_i},
\]

\[
U_{1i}' = \frac{\partial U}{\partial x_i} \geq 0,
\]

\[
U_{2i}' = \frac{\partial U}{\partial c_i} \leq 0.
\]

For convexity it is generally assumed that \( U_{1i}'' < 0 \) and \( U_{2i}'' < 0 \) (increasing marginal disutility of crime). This yields an upward sloping arrest “demand” schedule between criminal activity and law enforcement effort at the town level—conditional on the “effectiveness” of arrests on reducing crime \( dc_i/da_i \). As a consequence of convexity a greater derivative \( dc_i/da_i \) will shift this schedule rightward in \([c_i, a_i]\) space and lead the town to spend more and increase arrests. A smaller derivative discourages expenditure.
With each town using the marginal condition (7), we get a system of \( N \) “demand” equations in \([c_i, a_i]\) space that depict how increases in crime generate greater arrest expenditure. These are conditional on the values of \( dc_i/da_i \). This is then compared with the downward sloping “criminal supply” schedule faced by any individual town, as shown in Fig. 1. An MSA with greater fragmentation will have a greater \( N \) holding \( H \) fixed. This will potentially shift the demand schedule if \( N \) impacts the “arrest effectiveness” derivative \( dc_i/da_i \)—while it also shifts the supply schedule through the scale effect \( \alpha \).

4. Impact of fragmentation on arrest demand and criminal supply

Greater MSA fragmentation is effectively a reduction in average town size as each is a smaller share of the MSA. Any impact of town size on arrest demand will come through its impact on the arrest effectiveness derivative. To better understand this impact we can suppose there are two towns: “our” town 1 and “all others” 2. From (5) this simplification produces the following elaboration:

\[
\frac{dc_1}{da_1} = -c_1 h_1^\alpha L - (h_2 + a_2 h_2^\alpha L)(V'_{11}/V'_{22}) \quad \frac{(h_1 + a_1 h_1^\alpha L) + (h_2 + a_2 h_2^\alpha L)(V'_{21}/V'_{22})}{(h_1 + a_1 h_1^\alpha L) + (h_2 + a_2 h_2^\alpha L)(V'_{21}/V'_{22})}.
\]

(8)

Now as \( h_1 \) goes to zero, \( dc_1/da_1 \) approaches the displacement term \(- (V'_{11}/V'_{21})\). A “tiny” town has no effective impact on metropolitan wide incarceration. At the other extreme as \( h_2 \) approaches zero, \( dc_1/da_1 \) equals just the incarceration term \(-c_1 L/(h^{1-\alpha} + a_1 L)\) since displacement away from a very “large” town becomes effectively impossible.

In equilibrium we further assume Nash symmetry and this simplification implies: \( c_j = c, \ h_j = h = H/N, \ a_j = a, \ V'_{2j} = V_2' \) and \( V'_{1j} = V_1' \). With this the equations in (3–5) reduce to those in (9):
\[ \frac{dV^*}{da_i} = \frac{1}{N} \left[ \frac{-cLV'_2}{(H^{1-\alpha}N^{\alpha-1} + aL)} + V'_1 \right], \]

\[ \frac{dc_i}{da_i} = \frac{1}{N} \left[ \frac{-cL}{(H^{1-\alpha}N^{\alpha-1} + aL)} - \frac{V'_1(N - 1)}{V'_2} \right], \]  

\[ \frac{dc_j}{da_i} = \frac{1}{N} \left[ \frac{-cL}{(H^{1-\alpha}N^{\alpha-1} + aL)} + \frac{V'_1}{V'_2} \right]. \]  

Clearly as \( N \) increases, the magnitude of all the derivatives, \( dc_i/da_i \), \( dV^*/da_i \) and \( dc_j/da_i \) is reduced, whatever their signs. But greater fragmentation has an additional impact depending on the scale factor. If smaller towns are more effective at translating arrests into incarcerations (\( \alpha < 1 \)) then fragmentation will put away more criminals and the criminal utility (of those remaining) is more likely to increase. In (9) this takes the form of making the first expression within brackets (which is positively signed) larger for the derivative \( dV^*/da_i \). This also makes it more likely that the derivative \( dc_j/da_i \) will be negative. The opposite occurs if fragmentation (greater \( N \)) hinders incarceration (\( \alpha > 1 \)).

In (9), the impact of greater fragmentation (\( N \)) on own town arrest effectiveness takes a bit more effort. If (\( \alpha < 1 \)) but positive, then \( N \) increases both terms within brackets while at the same time it decreases the expression through the \( 1/N \) term. Its impact on the terms within brackets however is less than proportional while its impact through \( 1/N \) is proportionally inverse. The net effect must be to make \( dc_j/da_i \) smaller in absolute value.\(^3\) If (\( \alpha > 1 \)) then the term within brackets may not increase at all and the impact of greater \( N \) is clearly to reduce the magnitude of the derivative. In effect, greater fragmentation reduces the incarceration effect while at the same time increasing the displacement effect. The former always dominates. Hence the effectiveness of own town arrests is reduced and this generates a leftward (upward) shift in the “arrest demand” schedule (Fig. 1).

Of course while fragmentation is shifting demand leftward, it can shift supply in either direction. Again invoking Nash symmetry, expression (1) reduces to (10) below where the impact of \( N \) shifts this supply schedule upward if \( \alpha > 1 \) and downward if \( \alpha < 1 \).

\[ c = \frac{C}{(H + aLH^{\alpha}N^{1-\alpha})}. \]  

The empirical implications of the model are now quite straightforward if a bit imprecise. If fragmentation has no impact on arrest effectiveness through “X-Efficiency” then the leftward shift in the demand schedule clearly indicates that an MSA with greater fragmentation should see lower levels of resources devoted to law enforcement—and higher MSA wide crime. If small towns are more “X-efficient” at controlling crime, then the supply curve also shifts (downward) with the net result that resource expenditures are lower, but changes in crime are indeterminate. If small towns are less “X-efficient” at controlling crime, then the supply curve shifts upward with the net result being that crime is higher while changes in law enforcement resources are indeterminate. This is summarized in Table 1.

\(^3\) It is not much work to show that the second derivative \( d^2c_i/(da_i dN) \) is positive in algebraic sign as long as \( \alpha > 0 \) which is required.
5. Cross section data

The primary data base of the empirical section of the paper is a cross section of 236 US metropolitan areas. For each of these areas we obtained a wide range of data on population, income, poverty, the age distribution, climate, etc. (see below). This is slightly less than the total number of US metro areas because some data was occasionally missing, and as well, this data had to be matched to the list of MSAs from the LEAA and FBI.

For criminal activity, we used the FBI uniform crime reports for 1997, aggregated into two categories: property crime (burglary, larceny, theft) and violent crime (assault, rape, murder, robbery). This data is often used despite widespread misgivings about the under-reporting of crime. So-called “victimization surveys” simply would not have provided us with enough metropolitan areas. The FBI data was available from approximately 16000 agencies covering 253 MSAs.

The annual incidence of property crime in these MSA ranges from 5 per thousand to 101 per thousand. Violent crime ranges from 0.3 per thousand to 18 per thousand.

The year 1997 was chosen because every so often, the LEAA conducts a “Census” of all law enforcement agencies in the United States. This is not a regular survey and was last done in 1997 and involved approximately 24,000 agencies. An agency must employ more than 5 people to be interviewed. This survey is the only national systematic source of data on police expenditures. Included is limited information on total expenditures, and total employees, but with no evaluation of FTE (full time equivalency). Many enforcement employees are paid hourly and are part time, so this is a shortcoming of the census. This data was aggregated to the MSA level but excluded expenditures made by State and Federal agencies operating in the MSA. In effect it included only local municipal police, County Sheriffs and any enforcement activity by public authorities (e.g. transit police). The census shows that expenditure per capita for law enforcement ranges from $33 to $296 across the 236 metropolitan areas.

To supplement the LEAA data, we also gathered information from the government’s employment survey of average wages and earnings in the year 1997—for those employees in local public law enforcement agencies (occupational categories 61005, 63001, 63014). In our data, average hourly wages (across all law enforcement occupations) range from low values of near $9.50 in some Southern areas to as high as $32.00 in a few large metropolitan areas. Dividing this into the agency’s total budget we get some measure of the real resources (e.g. person “hours”) that each area puts into law enforcement.

Table 2 summarizes the data obtained and divides the variables into two categories: those most likely to represent demand side instruments and shift local law enforcement expenditure and those most likely to be supply side instruments and shift the supply of criminal activity. This division of course is far from certain, and we will discuss this in more detail in the following section.
Table 2
Variables, definitions

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avepolice</td>
<td>Average MSA police expenditure per capita</td>
</tr>
<tr>
<td>Aveex</td>
<td>Avepolice/wage</td>
</tr>
<tr>
<td>Aveprpcm</td>
<td>MSA property crime rate</td>
</tr>
<tr>
<td>Aveviocrm</td>
<td>MSA violent crime rate</td>
</tr>
</tbody>
</table>

**Demand**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage</td>
<td>Average MSA hourly wage of all local police employees</td>
</tr>
<tr>
<td>Perinc</td>
<td>MSA per capita income</td>
</tr>
<tr>
<td>Edu</td>
<td>Average years of education of the MSA population over 24</td>
</tr>
<tr>
<td>Landarea</td>
<td>Land area within MSA definition</td>
</tr>
</tbody>
</table>

**Supply**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Povrat</td>
<td>Fraction of MSA household below the “poverty” line</td>
</tr>
<tr>
<td>Unemp</td>
<td>MSA unemployment rate</td>
</tr>
<tr>
<td>Black</td>
<td>Fraction of MSA population of the Black race</td>
</tr>
<tr>
<td>Hispanic</td>
<td>Fraction of MSA population of Hispanic origin</td>
</tr>
<tr>
<td>Popover24</td>
<td>Fraction of MSA population over the age 24</td>
</tr>
<tr>
<td>Coolday</td>
<td>Average number of days/year “requiring air conditioning”</td>
</tr>
</tbody>
</table>

**Joint**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criagency</td>
<td>Number of MSA law enforcement agencies</td>
</tr>
<tr>
<td>Pop</td>
<td>MSA population</td>
</tr>
</tbody>
</table>

6. Cross section results

In each of the next three tables, we present regression results for one of the three dependent variables of interest: law enforcement effort (Aveex in Table 3), property and violent crime (Aveprpcm, Aveviocrm in Tables 4 and 5). The first three columns in each table are reduced form equations for that variable using a growing list of the exogenous variables in Table 2 that shift both the demand for law enforcement expenditures and the supply of property and violent crimes. As more variables are added between columns 1 and 2, the fits tend to improve but coflinearity sometimes takes a toll on statistical significance. An important distinction between columns 2 and 3 in each table is whether to include the average police wage rate of an MSA as another “exogenous” variable. The simple correlation of this variable with per capita income is quite high (0.86) and so it can be argued that these wage rates largely move with MSA income and cost of living. As such they plausibly represent an exogenous cost “shifter” rather than being an endogenous resource decision. Still we present all results with and without the wage variable.

In columns 4 and 5 of each table we offer up “structural” IV equations for the variable of interest where the instruments used are based on the assignments described in Table 2. This is done to try and identify how each schedule is shifting with greater fragmentation. On the demand side we use education level as a taste variable distinct from per capita income which represents ability to pay. This runs contrary to the recent argument by Lochner and Moretti [11] that education might be an important crime supply shifter as well. The wage rate obviously shifts expenditures or alternatively will negatively impact real resources. Land area has been argued by several authors to again impact the cost and difficulty of providing law enforcement resources (Newlon [12]). Socio-economic, racial, demographic, and poverty variables are assigned to the supply (crime generating) equation. The assumption is that poor economic conditions together with a younger minority population will all increase crime supply. There has been substantial
Table 3
Police resources per capita (Aveex)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
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<tr>
<td>Estimation</td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
<td>IV\textsuperscript{a}</td>
<td>IV\textsuperscript{b}</td>
</tr>
<tr>
<td>Constant</td>
<td>6.9e−04</td>
<td>6.9e−04</td>
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<td>−1.2e−03\textsuperscript{**}</td>
<td>−2.4e−04</td>
</tr>
<tr>
<td>Perinc</td>
<td>9.7e−08\textsuperscript{**}</td>
<td>1.3e−07\textsuperscript{**}</td>
<td>2.2e−07\textsuperscript{**}</td>
<td>2.3e−07\textsuperscript{**}</td>
<td>7.7e−08\textsuperscript{**}</td>
</tr>
<tr>
<td>Pop</td>
<td>1.6e−10\textsuperscript{**}</td>
<td>1.8e−10\textsuperscript{**}</td>
<td>2.2e−10\textsuperscript{**}</td>
<td>1.9e−10\textsuperscript{**}</td>
<td>3.9e−11</td>
</tr>
<tr>
<td>Povrat</td>
<td>5.5e−03\textsuperscript{**}</td>
<td>7.8e−03\textsuperscript{**}</td>
<td>5.0e−03\textsuperscript{**}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Criagency</td>
<td>−6.4e−06\textsuperscript{**}</td>
<td>−5.8e−06\textsuperscript{**}</td>
<td>−7.2e−06\textsuperscript{**}</td>
<td>−4.3e−06\textsuperscript{**}</td>
<td>−2.9e−06\textsuperscript{*}</td>
</tr>
<tr>
<td>Edu</td>
<td>1.7e−05\textsuperscript{**}</td>
<td>7.2e−06</td>
<td>1.5e−05\textsuperscript{*}</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>3.1e−07</td>
<td>8.5e−06</td>
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<td>0.27</td>
<td>0.36</td>
<td>0.40</td>
<td>0.15</td>
</tr>
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</table>

\textsuperscript{a} Instruments are full list of exogenous variables.
\textsuperscript{b} Instruments exclude wage.
\textsuperscript{*} Significant at the 10% level.
\textsuperscript{**} Idem, 5%.

Evidence that crime is also easier to commit in warmer climates and at warmer times of the year and so we include the number of “cooling days” (Jacob and Lefgren [8]). We allow MSA size and the number of crime agencies to shift both supply and demand schedules in the structural as well as reduced form equations.

Table 3 contains the equations for arrest demand or law enforcement resources. In the first column we use just 5 instruments from both sides of the model. All instrument signs are as expected. Per capita income increases expenditure as also is true of larger MSAs with higher poverty and minority concentration. Presumably these latter effects occur as these factors increase crime generation which then increases expenditure demand.

In the second column we expand the instruments. Here the only unexpected result is the unemployment variable which one would suspect should be associated with higher expenditure to counteract its impact on crime generation. Fit improves, but the significance of the minority variables suffers.

In the third column the addition of law enforcement wages provides a very significant boost to explaining real resource outlays—with the expected sign. We tend to regard this variable as exogenous, but it certainly could be argued that as resources increase, wages do as well while working up a regional labor supply curve.

In columns 4 and 5 there are two IV “structural” demand equations containing crime rates which use the supply instruments for identification (as so classified in Table 2). The equations have the expected sign with respect to the instrumented crime variable, and either property or violent crimes are significant statistically. Violent and property crime are very highly correlated, however, so while each works well in these equations, when included together they become insignificant.
Table 4
Property crime per capita (Aveprpcrm)

<table>
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<th>Variable</th>
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<th>3</th>
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R²          | 0.23     | 0.32     | 0.35     | 0.22  | 0.30  |
N           | 236      |          |          |       |       |

a Instruments are full list of exogenous variables.
b Instruments exclude wage.
* Significant at the 10% level.
** Idem, 5%.

What is most interesting is that in all of these equations, whether structural or reduced form, the impact of greater jurisdictional fragmentation is clearly negative and always significant. If we believe the model in the previous sections of the paper, this suggests that with more jurisdictions in an MSA, each tends to spend less because their impacts on regional incarceration become diminished. This result shows up in the “structural” equation as well and reinforces the conclusion that the changes created by fragmentation to the “displacement” effect are weaker and dominated by those to the incarceration effect.

In Table 4, we present the results for MSA property crime rates. In the first (reduced form) equation, all variables have the expected signs except for per capita income although it is not significant. In the second column, again most variables have the expected signs (if their roles are as depicted in Table 2), but the poverty variable becomes insignificant. Cooling days, the age distribution and education seems to be the variables that add explanatory power to the property crime rate.

In column 3, the addition of police wage rates also has the expected sign. If wages are an exogenous demand shifter (as in Table 2) then higher wages should lead to less real resources which then should increase crime in the reduce form. This is exactly what seems to happen. This view gets somewhat reinforced by column 4 and 5 where in the “structural” crime equations, police resources have the expected negative sign.

The most interesting result is that throughout all of these equations the number of law enforcement agencies has a consistent and significant negative impact on crime. As developed in the earlier model, and summarized in Table 1, this result can only be explained if greater fragmentation (a larger number of smaller jurisdictions) significantly shifts the criminal supply schedule downward (leftward in Fig. 1). This clearly seems to be the case in columns 4 and 5.
In Table 5 we get similar results with the violent crime rate. In the first two columns, all variables have the expected signs with the exception of per capita income, which in this case is significantly positive. The results in column 3 perhaps provide an explanation for this. When the police wage rate is included, per capita income becomes insignificant and the wage rate has the expected sign—raising the crime rate by presumably reducing real resources.

The “structural” violent crime equations also work, in the sense that the impact of greater police resources is negative whenever significant. The other exogenous variables continue to suggest that structurally, larger MSAs with young minority populations, in warmer climates and experiencing greater economic poverty or stress have more violent crime.

As in the property crime equations, every specification in Table 5 has the number of law enforcement agencies reducing the overall MSA crime rate, and at high significance levels. This is true whether the equation is a reduced form or a “structural” criminal supply equation.

Considerable experimenting was undertaken with the assignment of instruments in the “structural” models reported in the last two columns of Tables 3–5 and described in Table 2. While the assignment of some instruments may seem obvious (wage to the demand side, climate to supply), other’s are less clear. The assignment used and reported in the tables reflects that which tended to produce the best mix of both significant coefficients with anticipated effects. Thus for example, average education level has a plausible positive impact when used as a demand instrument, but no significant impact when used on the supply side. Similarly the fraction of the population that is young (1 − popover24) works as expected on the supply side but has no impact when assumed to shift demand. The racial variables have similar results with expected supply effects, but no significant impacts when assigned to demand.

Further experimenting was undertaken with respect to the MSA sample. A first test was to restrict the analysis to just MSAs with populations of over 400,000. This reduced the sample to...
just 83 observations and reduced the significance of the results, but qualitatively the conclusions of Tables 3–5 remained. In particular the number of crime agencies remained significantly negative in both resource and crime equations. In another test we remove those 19 MSAs that are effectively suburban-only areas (e.g. Riverside, Bergen-Passaic) and those that have obviously unique crime issues such as resorts (e.g. Atlantic City, Myrtle Beach) and college towns (e.g. Madison, Wisconsin). This had virtually no impact on the results.

Finally, we experimented with replacing the number of law enforcement agencies with the number of incorporated communities in each MSA. Since the simple correlation between these two is 0.96, the results were also virtually identical.

The point estimates in Tables 3–5 are stable enough to warrant examining in more detail. A typical large metropolitan area in the US (with 1.5 million people) has about 150 law enforcement agencies. Were the cities and towns in such an area to create a single consolidated law enforcement agency, the reduced form point estimates suggest the following ramifications. Law enforcement resources would increase by 33% from the sample mean of 0.003, property crime would increase by 40% from its mean of 0.04 and violent crime would increase by 75% from its mean of 0.004. All of these estimates of course are based on a linear model and we have not experimented with alternative functional forms.

7. **Why does fragmentation generate improvements in “X-efficiency”?**

The empirical results are completely consistent with the model presented—but only under a specific set of assumptions. The fact that greater fragmentation negatively shifts the demand for law enforcement resources is completely consistent with the carefully delineated model of criminal incarceration and spatial displacement. That said, we have provided little explanation of what is behind the seemingly quite strong increase in “X-efficiency” within a highly fragmented MSA.

One idea is to hypothesize that a larger number of smaller police departments somehow improves internal police efficiency through Tiebout type competition. Those agencies that do not perform well face an exodus of residents, loss of revenue, etc. This competitive pressure is clearly greater when there is fragmentation (i.e. many smaller jurisdictions). In many ways this is Hoxby’s [7] argument about schools. Pressure and competition from many nearby districts gives parents more options and so school districts operate closer to their production frontier.

Another source possible source of “X-efficiency” does not involve slack or better resource management, but instead emphasizes the important role of “local knowledge”—the basis of the whole “community policing” movement (Wilson [15]). It could be that small local police departments “get to know” their environs better and this is an important step in controlling crime. In this situation fragmentation is beneficial not because of competition, but more from some intrinsic “diseconomy to scale” that fragmentation helps to overcome.

Of course if there is some advantage like this, the question is why larger police department don’t decentralize more geographically and also reap the rewards of smaller scale. Why cannot a large single police department decentralize with independent neighborhood units? Isn’t this what “precincts” are supposed to do?

A possible explanation for why a large municipal agency does not operate like a system of independent police departments—despite the precinct system—involves a “political economy” story developed almost two decades ago by Behrman and Craig [1]. They argued that larger police departments face political pressure to allocate resources more uniformly across neighborhoods than would be dictated purely on efficiency grounds. In their model—in which criminals
are not mobile—efficiency would dictate strictly putting resources where crime originates. Of course a system of independent policy departments would do just this. In their type of model, metropolitan consolidation would lead to more spending in the suburbs (where it was not as productive), less in the inner city (where it is), higher crime and then greater spending overall. These authors present empirical evidence from within a major east coast city that this was the case for resource allocation across precincts. Their model however, does not lend itself to incorporating criminal mobility and criminal mobility is always assumed in more recent research.

If politically induced resource “misallocation” between areas is the explanation for our results then future empirical research might examine the actual patterns of spending across jurisdictions. Presumably, MSAs with greater fragmentation would exhibit more variation in law enforcement expenditure. The empirical problem of course would be to disentangle the behavioral effect from the obvious impact that consolidation has by construction when only town level data is available. By definition, a few large police departments have less variation in spending if data is only available at the jurisdictional level. Collecting precinct level data for 235 MSA would be near to impossible. For the moment then, this research has uncovered an important empirical observation—one that needs further explaining.

Acknowledgment

The author is indebted to the participants in the MIT Public Finance Workshop for helpful suggestions. He remains responsible for all results and conclusions.

References