

Crime and the Geography of the City: Measuring the Effect of Crime on Urban Residential Patterns

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Abstract

In this paper I use a novel urban geography model to estimate the effect of crime on residential and commuting patterns in the city. I estimate the residential amenities of various locations in the city of Chicago, then determine the effect of crime on these amenities. I also present a framework for thinking about the displacement effect of urban crime.

1 Introduction

The city has been a dominant feature of the human experience for over 8000 years. Cities bring tremendous benefits to their residents by providing easier access to markets, facilitating information exchange and learning, and encouraging socialization and the growth of communities. Cities also benefit non-residents by stimulating innovations—both technological and cultural—that find their way well beyond the city’s borders (Jacobs (1969)).

The rate of urbanization rapidly increased in the 19th century with the arrival of the industrial revolution. Today, roughly 80% of Americans live in cities, up from 40% in 1900 and 5% in 1790 (U.S. Census (2012)).¹ This percentage is similar throughout most of Europe and in much of the developed world, and the rate of urbanization is especially high today in developing countries.

Economists have been rigorously studying cities since the 1960s, and today urban economics is one of the most dynamic areas of research in economics. Urban economics can help us understand, among other things, why people move to cities, where people choose to live in cities, how land should be optimally allocated between residential, commercial, and industrial uses, and how much cities should invest in transportation infrastructure. Recent work in urban economics has borrowed heavily from the international trade literature, specifically general equilibrium models with gravity (Allen, Arkolakis, and Li (2015) and Ahlfeldt, Redding, Sturm, and Wolf (2014), which will henceforth be referred to as AAL and ARSW). The motivation for this is that cities can be modeled as sets of locations that trade with one another, just as countries do. A major difference, however, between the models used in international trade and urban geography is that city dwellers typically work in locations away from their homes; therefore studying commuting patterns opens a new realm of possibilities in the analysis of cities.

For all of their many alluring qualities, there are drawbacks to living in the city: land is much scarcer and therefore much more expensive than in the countryside; cities have historically suffered from air and water pollution, and many still do; finally, cities typically have much higher crime rates than rural areas, especially in the United States over the last fifty years. While crime generally doesn't prevent people from living in metropolitan areas, it *does* affect where they choose to live within cities; for instance, high "inner city" crime rates often drive wealthier residents to the suburbs. The "flight" of residents (especially white residents) out of American cities during the 1950s and 1960s further exacerbated many of the problems that led to high urban crime rates in the first place

¹The U.S. Census defines a city as any populated area with a population of over 2,500. Colloquially, we usually think of cities as being significantly larger than this, so perhaps the more relevant statistic is that 55% of Americans live in metropolitan areas with populations of over one million.

(Cullen and Levitt (1999)). The trend has been reversing in many cities over the last 20 years, but crime still plays an important role in keeping people (especially the middle and upper classes) out of certain neighborhoods. And it remains an unfortunate part of the lives of many people who are not able to afford an escape.

Gary Becker pioneered the economic study of crime with his 1968 paper on the economic motivations behind crime (Becker (1968)), and since then there have been numerous papers published on the causes and effects of crime in society at large (for instance, Donohue and Levitt (1999), Reyes (2007), and Dahl and DellaVigna (2009)). Some economists have also analyzed the effects of crime on city rents and wages (e.g., Roback (1982)), while Cullen and Levitt (1999) examines the effect of crime on urban outmigration. However—to the best of my knowledge—there has been no work done on the effects of crime on *intracity* residential patterns. Specifically, the questions I would like to address are: how does the crime rate affect the desirability of a neighborhood? And how do changes in desirability affect where people choose to live, as well as agents' welfare? There are also a number of interesting questions concerning the drivers of high crime rates in cities (many of which are discussed qualitatively in Jacobs (1961)); for instance, how does urban blight affect crime rates? Or how do zoning and other planning policies affect crime rates? The causes of crime are complex and I will not be able to address that aspect in this paper. Therefore I take crime rates as exogenous throughout.

In the next section I introduce a very simple monocentric model to illustrate the effect of neighborhood desirability on residential patterns. In the third section I introduce a more complete model (following AAL and ARSW) that lifts the monocentricity assumption. This is the model that I use to estimate neighborhood amenities, and then the effects of crime, for the city of Chicago in the fourth section. The fifth section presents and discusses the empirical results, and the sixth section concludes.

2 A Simple Model

Suppose we have a monocentric, radially symmetric city of radius R , with a central business district (CBD) at the center, $r = 0$. The city is populated by L workers, all of whom

work in the CBD and choose how far away to live. Each worker's utility comes from consumption of a single final good (q), consumption of housing (h), and neighborhood amenity (B), discounted by a commuting cost (d). Radial symmetry implies that all variables are functions of r only; furthermore, I assume q to be independent of r altogether. Assuming Cobb-Douglas form for consumption, the utility of a worker living at radius r is given by

$$u(r) = \frac{B(r)}{d(r)} q^\beta h(r)^{1-\beta}.$$

At equilibrium, all workers' utilities are the same (otherwise they would have an incentive to move), so for any two $r_1, r_2 < R$, we have

$$u(r_1) = u(r_2) \iff \frac{B(r_1)}{d(r_1)} h(r_1)^{1-\beta} = \frac{B(r_2)}{d(r_2)} h(r_2)^{1-\beta}.$$

If we take B to be constant, the quantity of housing consumed is proportional to the commuting cost: $h(r) = \bar{U} d(r)^{1/(1-\beta)}$, where \bar{U} is the equilibrium utility of each worker. The total quantity of housing is assumed to be the area of the city, $H = \pi R^2$, so we must have that

$$H = \int_0^R h(r) 2\pi r dr = \bar{U} \int_0^R d(r)^{1/(1-\beta)} 2\pi r dr.$$

Suppose now that, due to high crime rates near the CBD, B isn't constant but increases with radius (for instance, $B(r) = \sqrt{r}$). Housing consumption becomes $h(r) = \bar{U} (d(r)/B(r))^{1/(1-\beta)}$ and the population density $L(r) = 1/h(r)$ is now smaller than it was before near the center of the city.² \bar{U} is now given by

$$\bar{U} = H \left(\int_0^R (d(r)/B(r))^{1/(1-\beta)} 2\pi r dr \right)^{-1}.$$

If we normalize $B(r)$ (such that the average value, $1/H \int_0^R B(r) 2\pi r dr$, is 1 in all cases), it is clear that, at least for some $d(r)$, \bar{U} decreases when B is lower near the center of the

²Market-clearing implies that rent must also be inversely proportional to $h(r)$.

city. This can be further seen by considering average commuting cost, which is given by

$$\bar{d} = \int_0^R L(r) d(r) 2\pi r dr.$$

Since labor is now pushed outward from the center of the city (but all workers still commute to the CBD), average commuting costs increase.

To consider a concrete example, suppose that, in the constant amenity case, $R = 1$, $B(r) = 1$, $d(r) = e^r$, and $\beta = 1/2$. Then, \bar{U} is given by

$$\bar{U} = \pi \left(\int_0^1 e^{2r} 2\pi r dr \right)^{-1} \approx 0.238$$

and $L(r) = \bar{U} e^{-2r}$. Suppose now, instead, that $B(r)$ is $1/2$ for $0 \leq r < 1/2$ and $7/6$ for $1/2 \leq r < 1$ (these values ensure that B has mean value 1, as before). In this case,

$$\bar{U} = \left(\int_0^{1/2} e^{2r} r dr + \frac{7}{3} \int_{1/2}^1 e^{2r} r dr \right)^{-1} \approx 0.219$$

and $L(r) = \bar{U} e^{-2r} B(r)^2$. So the welfare of *all* residents declines, even though more people now live in higher-amenity areas (as we can see in Fig. 1 in the Appendix).

There are several intuitive takeaways from this toy model. Firstly, and rather obviously, crime can decrease utility directly by decreasing the amenity of living in certain parts of the city. Crime also creates a less direct displacement effect, whereby people have to move further away from the city to live in lower-crime areas, and so their commutes become longer. Furthermore, if we assume the radius of the city to be fixed, crime will squeeze more people into lower-crime areas, increasing the demand for housing and therefore the rent in these areas. And if the city expands to accommodate the flight outward (and ease the demand for housing), commuting costs will increase further.

3 Complete Model

The complete model I will use from here on out closely follows the general equilibrium models of AAL and ARSW, which in turn extend the canonical Alonso-Mills-Muth model

(Alonso (1966), Mills (1967), and Muth (1969)) to urban areas with arbitrary geographies (lifting the monocentricity assumption).

I consider a city that is a set of locations (or blocks) indexed $i = 1, \dots, S$. Blocks differ in their productivities (A_i), residential amenities (B_i), quantities of residential and commercial floorspace (H_i^R and H_i^F , respectively), and locations (which determine their proximity to other blocks, and therefore travel times t_{ij}). As we will see, urban crime enters in both the productivity and amenity terms. The city's labor force has total measure \bar{L} .³ I assume that trade across locations is costless (that is, the iceberg trade cost is $\tau_{ij} = 1$ for all location pairs i, j); this is a reasonable assumption given the relative proximity of locations within the city. Furthermore, I assume that the price level at all locations is the same; significant deviations from this assumption are unlikely to occur at equilibrium when locations are so close to each other (as the city's residents could then choose to do their shopping in another neighborhood).

Given knowledge of the above characteristics (and an idiosyncratic utility shock), each worker chooses a residence location i and a work location j , as well as how much to consume of both housing (residential floorspace) and a single final good. Firms choose how much labor to hire and how much commercial floorspace to rent; the economy is assumed to be perfectly competitive so that all firms have zero profits.

3.1 Workers

Workers have Cobb-Douglas utilities that depend on residential amenities, commuting costs, and consumption of housing and final goods, as well as an idiosyncratic shock. That is, following ARSW, worker ω living in i and working in j will have utility

$$u_{ij}(\omega) = \frac{B_i}{d_{ij}} q_{ij}(\omega)^\beta h_{ij}(\omega)^{1-\beta} z_{ij}(\omega), \quad (1)$$

³Unlike ARSW, which treats workers as perfectly mobile within the larger economy, I treat the city as a closed economy and the supply of labor within the city as fixed; in other words, I take it for granted that all workers have decided to live in the city.

where B_i is the residential amenity (the attractiveness of a location, independent of its proximity to the agent's workplace), $d_{ij} = e^{\kappa t_{ij}}$ is the commuting cost (where t_{ij} is the travel time between locations i and j), $q_{ij}(\omega)$ is the worker's consumption of a single final good, $h_{ij}(\omega)$ is the worker's consumption of residential floorspace, and $z_{ij}(\omega)$ is a stochastic term to account for idiosyncratic preferences across workers. As in both AAL and ARSW, I assume that $z_{ij}(\omega)$ is drawn from a Fréchet distribution:

$$Pr[z_{ij}(\omega) < u] = e^{-E_j u^{-\theta}}, \quad E_j > 0, \quad \theta > 0,$$

where E_j is the workplace amenity and θ is a shape parameter.

A location's crime rate enters the worker's utility through B_i , so—if we wish—we can explicitly rewrite these in terms of the crime rate at location i , c_i :

$$B_i = \bar{B}_i c_i^{-\gamma}, \quad \gamma > 0. \quad (2)$$

To see how an agent's utility changes in response to an increase in the crime rate, we can take the partial derivative of u_{ij} with respect to c_i :

$$\frac{\partial u_{ij}(\omega)}{\partial c_i} = \left(\frac{q_i(\omega)^\beta h_i(\omega)^{1-\beta} z_{ij}(\omega)}{d_{ij}} \right) \frac{\partial B_i}{\partial c_i} = -\gamma \frac{\bar{u}_{ij}(\omega)}{c_i},$$

where $\bar{u}_{ij}(\omega)$ is the baseline utility before the increase in crime. From this, it is easy to see that higher-income workers (reflected in higher values of q and h , and therefore \bar{u}) are more strongly affected by increases in crime rates, which is part of the reason lower-income workers tend to be overrepresented in higher-crime areas.

More generally, we might want to use a composite index of crime, as agents are likely to be more sensitive to certain types of crime than others. For instance, while both violent crime and property crime generally decrease the amenity of a neighborhood, we would expect violent crime to have a more significant effect. Violent crime can be further sub-divided by type (e.g., homicide, robbery, or assault) or incentive (gang-related or

otherwise). In general, given n types of crime, we can create a composite index \bar{c}_i :

$$\bar{c}_i = c_{1i}^{\gamma_1} c_{2i}^{\gamma_2} \cdots c_{ni}^{\gamma_n}, \quad (3)$$

where c_{ki} is the rate of crime k at location i , and γ_k is agents' relative sensitivity to this type of crime.

Alternatively, we might write the effect of crime as an exponential decay factor,

$$B_i = \bar{B}_i \exp(-\delta c_i), \quad \delta > 0, \quad (4)$$

and instead use a composite index \tilde{c}_i that is just a weighted sum of crime rates:

$$\tilde{c}_i = \delta_1 c_{1i} + \delta_2 c_{2i} + \cdots + \delta_n c_{ni}. \quad (5)$$

The indirect utility of living in i and working in j can be found by solving a straightforward optimization problem over $q_i(\omega)$ and $h_i(\omega)$:

$$\max_{q_i(\omega), h_i(\omega)} q_{ij}(\omega)^\beta h_{ij}(\omega)^{1-\beta} \quad \text{such that} \quad q_{ij}(\omega) + r_i h_{ij}(\omega) \leq w_j,$$

where r_i is the rent (price of residential floorspace) at i and w_j is the wage paid at j . (The good has price $p = 1$.) Since utility is Cobb-Douglas, the problem is solved with $q_{ij}(\omega) = \beta w_j$ and $h_{ij}(\omega) = (1 - \beta)w_j/r_i$. So, to a constant multiple, the indirect utility is

$$u_{ij}(\omega) = \frac{B_i w_j z_{ij}(\omega)}{d_{ij} r_i^{1-\beta}}. \quad (6)$$

Given this, we can find the probability that a worker chooses to live in i and work in j . Following the usual approach in discrete-choice modeling (and AAL and ARSW), we get

$$\pi_{ij} = \frac{E_j(B_i w_j)^\theta (d_{ij} r_i^{1-\beta})^{-\theta}}{\sum_{r=1}^S \sum_{s=1}^S E_s(B_r w_s)^\theta (d_{rs} r_r^{1-\beta})^{-\theta}}. \quad (7)$$

π_{ij} reflects what we would expect from intuition: all else equal, a worker is more likely to live in a neighborhood with higher amenity, lower rent, and shorter commutes to work

locations; similarly, he is more likely to work in a location with higher amenity, higher wages, and shorter commutes to residential areas.

It becomes easier to estimate parameters and fixed effects if we can sequentially eliminate residential and workplace characteristics, which can be done by summing over residential and workplace locations. The probability of residing in i conditional on working in j , $\pi_{Ri|j}$, is given by

$$\pi_{Ri|j} = \frac{\pi_{ij}}{\sum_{r=1}^S \pi_{rj}} = \frac{E_j(B_i w_j)^\theta (d_{ij} r_i^{1-\beta})^{-\theta}}{\sum_{r=1}^S E_j(B_r w_j)^\theta (d_{rj} r_r^{1-\beta})^{-\theta}} = \frac{B_i^\theta (d_{ij} r_i^{1-\beta})^{-\theta}}{\sum_{r=1}^S B_r^\theta (d_{rj} r_r^{1-\beta})^{-\theta}}. \quad (8)$$

Notice that the workplace characteristic terms E_j and w_j cancel because the sum in the denominator is over residential locations only. Intuitively, we expect that $\pi_{Ri|j}$ should only depend on the characteristics of i , as well as the distance between i and j , but not on the features of j , since those are common to all agents who work there. Similarly, the probability of working in j conditional on living in i is given by

$$\pi_{Wj|i} = \frac{E_j(w_j/d_{ij})^\theta}{\sum_{s=1}^S E_s(w_s/d_{is})^\theta}. \quad (9)$$

As reliable micro-level wage data is lacking, I focus my analysis on determining B_i ; I neglect E_j from here on out.

3.2 Firms

Although this paper isn't concerned with production per se, it is worth briefly examining that aspect of the model. Firms are assumed to have Cobb-Douglas production functions; the amount of the good produced at location j is given by

$$y_j = A_j L_j^\alpha H_j^{1-\alpha},$$

where A_j is the productivity of j , L_j is the quantity of labor employed at j , and H_j is the amount of commercial floorspace (capital) at j . The zero-profit condition requires that

$$y_j - w_j L_j - r_j^F H_j = 0,$$

where r_j^F is the price of commercial floorspace. It follows that

$$w_j = \frac{\partial y_j}{\partial L_j} = \alpha A_j \left(\frac{H_j}{L_j} \right)^{1-\alpha},$$

$$r_j^F = \frac{\partial y_j}{\partial H_j} = (1 - \alpha) A_j \left(\frac{L_j}{H_j} \right)^\alpha.$$

What role could the crime rate play here? Crime can interact with production in several ways: property crime can devalue a firm's capital; both violent crime and property crime can target workers, reducing the effective units of labor. Both of these effects can be captured by rewriting the productivity as $A_j = \bar{A}_j c_j^{-\zeta}$, which allows us to see how an increase in crime may affect wages and the price of commercial floorspace. All else equal, a higher crime rate decreases both the wage and the commercial rent. Since firms in j will hire a smaller labor force when productivity is lower *and* fewer workers will choose to work in j in response to a fall in wages (nevermind the crime rate's impact on workplace amenity E_j), L_j will shrink and production will become more capital-intensive.⁴

4 Estimation Procedure

4.1 Estimating Residential Amenity

Given data on commuting flows, travel times, and residential floor prices, we can use (8) to estimate the model parameters θ and κ , as well as the residential amenities B_i . Taking

⁴Indeed, high-crime areas tend to attract relatively little labor, and industry there often takes the form of depots and warehouses. Of course, crime is one of several factors that can account for this trend.

the logarithm of this equation (and recalling that $d_{ij} = e^{\kappa t_{ij}}$), we get

$$\begin{aligned}\log \pi_{Ri|j} &= \theta(\log B_i - \log d_{ij} - (1 - \beta) \log r_i) + a_0 + \epsilon_{ij} \\ &= \theta(\log B_i - \kappa t_{ij} - (1 - \beta) \log r_i) + a_0 + \epsilon_{ij},\end{aligned}\tag{10}$$

where a_0 is a scaling constant that corresponds to the denominator of (8) and ϵ_{ij} is a stochastic (normally distributed) error term, with expectation 0.

4.1.1 Description of Data

The city of Chicago (which had a population of 2,695,598 as of the 2010 Census) is divided into 801 census tracts, two of which are occupied by O'Hare and Midway International Airports (and have zero population). Excluding these two tracts, there is considerable variety in the tract sizes and populations: the largest tract is almost 16.9 square kilometers in area, while the smallest is 0.01 sq. km (neglecting water); the average tract area is 0.71 sq. km. The most populous tract has a population of 16,375, while the two least populous tracts (excluding airports) both have zero population; the mean tract population is 3,400.

Additionally, Chicago is divided into 77 community areas, the result of an initiative by the Social Sciences Research Committee at the University of Chicago in the 1920s (Chicago (2016)). Community areas range in population from just under 3,000 residents to just under 100,000, and, on average, each community area encompasses roughly ten tracts. Each tract falls within the boundaries of one community area, making it relatively easy to transform data between the two levels.

Commuting Data I use commuting data from the U.S. Census Bureau's Longitudinal Origin-Destination Employment Statistics (LODES), which uses unemployment insurance filings by businesses to determine the flow of workers from place of residence to workplace (U.S. Census Bureau (2015)). The raw data gives commuting flows at the level of the census block for the entire state of Illinois, which is both too detailed and too expansive for my purposes. I therefore aggregate by census tract and keep only the pairs of locations that represent commutes entirely within the city of Chicago. The assumption that the

city is a truly closed economy does—to an extent—fall short here, as there are a number of people who commute from or to locations outside of the city proper. However, if we take $\pi_{Ri|j}$ to be the proportion of people working in j who live in i , *conditional on living in the city*, we see that all of the proportions are simply scaled by a constant. Therefore, commutes into the city should have no effect on the parameters of interest.⁵

What about commuters who live in Chicago but work outside of the city? Neglecting these workers *will* have an effect on the calculated amenities, because they it lead to over- (or under-) estimation of the average commuting times for a given residential location. For instance, if a large number of people living near the city limits work outside of the city, but the commuting data only gives the flows within the city (and primarily to the CBD), the estimation procedure might overestimate average commuting times and therefore inflate the residential amenities. However, since Chicago is largely a monocentric city with a commerce-heavy CBD, such commutes out of the city represent a minority share of commuting flows.⁶

Finally, because the commuting flow data for a given year does not encompass all workers (but over 90% nonetheless) and therefore is prone to some measurement error, I aggregate five years of commuting data (from 2010 to 2014), on the reasonable assumption that commuting patterns have changed very little over this period. Still, just over half of elements in the tract commuting matrix L_{ij} are empty, which is unsurprising considering that there are $799^2 = 638,401$ total origin-destination pairs and just over 3 million total intra-city recorded commutes over the five-year period. On average, that amounts to roughly ten commuters per origin-destination pair, but some commutes are, of course, much more common than others (the highest commuting flow value is nearly 25,000).

Travel Times For travel times, I use the results of the fast-marching method (FMM) from AAL. FMM uses the concentration of roads, rails, and bus routes at each given

⁵Here’s an easy way to think about it: suppose everyone works in one location (the CBD) and there are two residential locations within the city and one outside it. When comparing the amenities of the two locations in the city, we’re only interested in how the proportions of commuters to the CBD from *these two locations* compare, even if the location outside of the city is responsible for the bulk of commuters to the CBD.

⁶In 2014, about 63% of commutes were between locations within the city. Furthermore, in nearly 96% of city tracts, a majority of the laborers worked in the city.

location on a grid to estimate the time required to traverse that location, then finds the shortest route between two points. AAL reports a close correlation between the results of FMM and the predicted travel times, as determined by Google Maps. Since AAL uses travel time data at the level of the block group, I average the pairwise data across tracts.

To account for commutes using both car and public transportation, I follow AAL and estimate the mean travel time using

$$t_{ij} = -\frac{1}{\lambda} \ln \left(0.5 \left(\exp(-\lambda t_{ij}^{\text{car}}) + \exp(-\lambda t_{ij}^{\text{public}}) \right) \right),$$

where a choice of $\lambda = 0.115$ is consistent with the fact that 12% of Americans commute using public transportation.⁷

We can compute the average (one-way) commuting time for a resident of location i by taking a weighted average of all commuting times: $\bar{t}_i = (1/L_{Ri}) \sum_{s=1}^S L_{is} t_{is}$, where L_{Ri} is the total size of the labor force that resides at i . Visualizing these averages on a map (Fig. 2) further suggests that Chicagoans generally commute to the CBD, as average commutes increase with distance from the CBD (and there is considerable radial symmetry).

Residential Rent I obtained rent data from the U.S. Census' American Community Survey (ACS), collected between 2010 and 2014. As this is a survey, not a census, the data are estimated from the residents who responded at least once over the course of five years (the surveys are conducted annually, and the 5-year ACS surveys include the results of all surveys for the preceding five years).

The ACS includes data on median (monthly) rent and aggregate (monthly) rent for each census tract. Additionally, it reports the median number of rooms per housing unit, the percentage of housing units that are vacant (or renter-occupied), and the distribution of housing age, among other characteristics that are of less interest to us.

There are several ways to approximate the residential floor price. The most direct approach would be to divide the total rent paid by the total residential floorspace (renter-occupied) for each tract. However, we run into the difficulty of computing the renter-

⁷This figure might be higher for a large city like Chicago; nonetheless, increasing λ would only have a negligible affect on my results, as car and public transportation times are strongly correlated.

occupied floorspace. The city of Chicago provides GIS data on footprints (and number of stories) for each building, which allows us to approximate the square footage of each building; it also provides detailed zoning data. However, a number of buildings (especially in the downtown area) are mixed-use, so calculating the residential square footage can only be done very approximately, at best. Most types of commercial and business zoning allow residential units above the ground floor; however, this by itself does not mean that there *are* residential units in these buildings. Furthermore, the architecture of many buildings makes it difficult to accurately calculate the square footage using the footprint and stories data alone, and this can create a significant discrepancy (especially for some of the taller buildings in downtown, like Sears Tower and the John Hancock Center).

A second approach is to use the median rent per room, which is (roughly) the median rent divided by the median number of rooms (per housing unit) for each tract. Of course, this approach rests on the assumption that room sizes are comparable across the city, which is not always true (we would expect rooms to be smaller near downtown and larger at the city's peripheries). Nonetheless, the variation in room sizes is probably relatively negligible compared to the calculated median rent per room, which varies significantly across the city (from around \$60 in some of the less desirable neighborhoods to over \$600 in neighborhoods around the CBD). As a slight variation on this approach, I also consider the *mean* rent per room, which I calculate by dividing the aggregate rent for each tract by the number of housing units, and then by the median number of rooms per unit (which I assume to be very close to the mean).

Because of the difficulty of computing residential floorspace with sufficient precision, I limit my analysis to the second method above (median and mean rents per room). The last missing piece of information is the value of β , for which I use 0.62, as in AAL; this is consistent with the fact that, on average, Chicagoans spend 38% of their income on housing.

4.1.2 Accounting for Tract Size

Notice that the commuting flow equation (7) does not account for differences in sizes between the tracts. Suppose, for instance, that there are two residential tracts with very similar characteristics (amenity, rent, proximity to workplaces, density of residential floorspace, etc.). If one tract is twice as large as the other (in area, and therefore in quantity of housing), we would expect this tract's commuting flows to be twice as large. As I've mentioned, tracts vary dramatically in size, so it is critical to account for this factor. However, the best way to address this is not immediately obvious.

One possible approach is to use the number of housing units per tract, information which is readily available. The shortcoming of this approach is that it treats housing as exogenous, when, in fact, housing supply often responds to demand. In other words, highly desirable neighborhoods are going to have more housing because there are more people who want to buy it. (7) already accounts for the primary factors (amenity and location) affecting neighborhood desirability, so this cannot be the correct approach.

Another possible approach is to simply use the area of each tract (minus any bodies of water). This is quite reasonable, except that not all land has the potential to be used residentially. We can instead consider the area of residential (and mixed) zoning within each tract. The shortcoming of this approach is that zoning can be a response to market factors—it is not purely exogenous. City planners might increase residential zoning in a given neighborhood when it becomes clear that more people would like to live there. However, nearly all land away from the CBD (and several industrial corridors) is already zoned for residential (and mixed) use, and there is little potential for planners to change the zoning type.⁸ Therefore we can treat this quantity as exogenous.

A very similar approach is to use the total area of each tract, minus the area of water and green spaces, like parks, schoolyards, and cemeteries. While residential and commercial zoning may respond to demand, some areas are clearly off limits to development, as most green spaces are near-permanent fixtures of a neighborhood, sometimes upwards of a century old.

⁸Most likely, planners would change the type of residential zoning to allow for higher density construction; but I consider all types of residential zoning together, so this distinction is irrelevant.

If we let K_i denote the “capacity”—however we define it—of location i , (8) becomes

$$\pi_{Ri|j} = \frac{K_i B_i^\theta (d_{ij} r_i^{1-\beta})^{-\theta}}{\sum_{r=1}^S K_r B_r^\theta (d_{rj} r_r^{1-\beta})^{-\theta}}.$$

(10) can be adjusted accordingly by scaling $\pi_{Ri|j}$; that is, the left side becomes $\log(\pi_{Ri|j}/K_i)$.⁹

The full regression equation is then given by

$$\log(\pi_{Ri|j}/K_i) = a_0 + \theta \log B_i - \theta \kappa t_{ij} - \theta(1 - \beta) \log r_i + \epsilon_{ij}. \quad (11)$$

For the purposes of estimation, this model can be written as

$$y_{ij} = a_0 + a_{1i} + a_2 t_{ij} + a_3 x_i + \epsilon_{ij},$$

where $y_{ij} = \log(\pi_{Ri|j}/K_i)$, a_{1i} is the fixed effect $\theta \log B_i$, and $x_i = (1 - \beta) \log r_i$. θ and κ can be estimated using $\hat{\theta} = -\hat{a}_3$ and $\hat{\kappa} = \hat{a}_2/\hat{a}_3$. The estimated amenity is then given by $\hat{B}_i = \exp(\hat{a}_{1i}/\hat{\theta})$.

Finally, in addition to the two airport tracts, I exclude tracts with fewer than 1000 residents or residential areas of less than 0.1 square kilometers, as these are prone to large errors in the survey rent data. I also exclude the tract dominated by Cook County Jail, as most of its residents have exceptionally short commutes.

4.2 Estimating the Effect of Crime

We can then compute the effect of crime on residential amenity. Specifications (2) and (4) lend themselves to the following log-log and log-linear models:

$$\log B_i = \log \bar{B}_i - \gamma \log c_i = \alpha_0 - \gamma \log c_i + \beta \mathbf{X}_i, \quad (12)$$

$$\log B_i = \log \bar{B}_i - \delta c_i = \alpha_0 - \delta c_i + \beta \mathbf{X}_i, \quad (13)$$

⁹Of course, (7) would be modified by including both the residential capacity of i and the workplace capacity of j .

where \mathbf{X}_i is a vector of controls (which I describe below). Recall from before that, when considering more than one crime rate, we can write

$$\log \bar{c}_i = \bar{\gamma}_1 \log c_{1i} \cdots \bar{\gamma}_n \log c_{ni},$$

$$\tilde{c}_i = \tilde{\delta}_1 c_{1i} + \cdots + \tilde{\delta}_n c_{ni},$$

for the two specifications. Therefore, according to the log-log specification, the total effect on amenity of crime rate c_{1i} is given by $-\gamma \bar{\gamma}_1 \log c_{1i}$, while for the log-linear specification, the effect is $-\delta \tilde{\delta}_1 c_{1i}$.

4.2.1 Crime Data

Detailed crime data is provided by the city of Chicago. The data set includes information on characteristics such as crime location, time, and type, among others, for all crimes reported to the Chicago Police Department. While some crimes do go unreported, we can assume that the more severe ones—namely violent and property crimes, which are the focus of this analysis—have high reporting rates, in low-crime and high-crime neighborhoods alike. Of course, some crimes, like minor theft and battery, may be underreported in neighborhoods where they are commonplace. I assume that the effect of underreporting is negligible across the types of crimes I am considering.

I use crime data over a six-year period, from 2009 to 2014. Since my commuting and rent data are from 2010 to 2014, it is reasonable to assume that agents' choices of residential locations over this period were largely influenced by crime rates during the same period, and one year prior.¹⁰ I consider three types of crimes: homicides, non-homicide violent crimes, and property crimes.¹¹ Using ArcGIS, I aggregate all occurrences of these crimes within each tract.¹²

¹⁰Perhaps agents' decisions were also informed by the period of five or so years before 2010, in which case it would be fair to include 2005 through 2008 as well. Excluding these years should have only a small effect, as crime rates have remained relatively constant during this period.

¹¹Following the definitions of the FBI's Uniform Crime Reporting protocol, violent crimes include murder (homicide), rape, robbery, and aggravated assault; property crimes include burglary, larceny-theft, motor vehicle theft, and arson.

¹²A small number (less than 1%) of the crimes were missing location information in the raw data set and so were not included in the aggregation.

Crime rates are typically given by annual number of incidents per 100,000 residents. Therefore I compute the crime rates by dividing the crime counts by six (for an annual average) and the tract populations (from the 2010 Census), and multiplying by 100,000. While this is the standard definition of a crime rate, it can be misleading. Consider, for instance, the heart of Chicago's CBD, which—by this definition—has a violent crime rate of over 3000 per 100,000, on par with some of the city's most dangerous neighborhoods. The reality, however, is that while this tract has a relatively small residential population (just over 4000), it has a very high number of laborers (over 300,000). It's likely that the majority of crime victims in the CBD are not residents but workers (or other visitors), so the crime rate is misleading, as it appears to inflate the probability of being a victim (which is the quantity people are *actually* interested when deciding where to live). Alternatively, we can take the crime rate to be the number of incidents per 100,000 residents *and workers*, which rests on the assumption that workers and residents are targeted with equal probability.¹³ This definition also has its shortcomings, so for the purposes of this paper I use the traditional definition for crime rates.

On a final note, I disregard the circumstances of the crimes in my analysis. Much of Chicago's violence (especially homicides) is tied to gangs, although since the 1990s, Chicago's gangs have splintered into numerous factions, making it difficult to discern gang-related incidents from non-gang crimes.¹⁴ The distinction might not be very useful: while it's true that gang violence is less likely to affect residents who are not affiliated with any gangs, the fear of being caught in the crossfire or having to witness turf wars near one's home is still likely to have a pronounced effect on agents' residential preferences.

Whether or not crimes are domestic might also affect agents' assessment of the risks associated with living in a given neighborhood, as domestic crimes would not be seen as dangerous for outsiders as street crimes. While the data indicates which crimes are domestic, I disregard this information, as it is unlikely to have a significant effect on the

¹³The reasonableness of this assumption depends on many factors. A very simple way to think about it is this: the majority of crimes occur between the 6 am and midnight, and workers are usually present for 8 of those hours (while most residents are gone during the same period of time). The presence of visitors throughout the day (who can be assaulted or robbed) and streetfront businesses (which can be burglarized) also affects the incidence of crime.

¹⁴This information is not reported in the crime data released by the city.

calculated crime rates.¹⁵

4.2.2 Controls

There are a number of other factors affecting residential amenity that may not be orthogonal to crime rates. These include housing age, vacancy rates, quantity of neighborhood greenspace (or open space), proximity to water (Lake Michigan in this case), proximity to commercial areas, and quality of neighborhood schools.

Approximate mean housing age and vacancy rates can be calculated using data from the ACS.¹⁶ The directions of causation between vacancy rates, crime rates, and residential amenity are not immediately clear; high crime rates might lead to higher vacancy rates, and so there might be significant collinearity between the two variables. Nonetheless, it is important to distinguish between the amenity effects of crime and the effects of *blight*, which can typically be seen in vacancy rates and may or may not be tied to crime.¹⁷

For green space, I use ArcGIS to compute the percentage of each community area covered by parks and other green areas. I move to the level of the community area because tracts are too small to give a good sense of how green a neighborhood is (many tracts have little to no green space themselves but are immediately adjacent to parks). I also use ArcGIS to compute the shortest straight-line distance from each tract to Lake Michigan.

Commercial areas are also expected to increase amenity, and I treat it as I treated green space: I calculate the proportion of land that is zoned commercially at the level of the community area. I also account separately for travel time to downtown (using the results of the fast marching method from earlier), since downtown Chicago's flurry of entertainment and shopping venues makes it a popular destination for tourists and residents alike.¹⁸

¹⁵Less than 13% of reported crimes are domestic.

¹⁶Vacancy rates are reported directly. Mean housing age can be calculated (approximately) from the distribution of ages provided in the survey.

¹⁷Wilson's "broken windows hypothesis" is that urban blight (vacancy, dilapidation, etc.) itself leads to higher crime rates (Wilson (1982)).

¹⁸It might seem that I am again adding the commuting cost from earlier, and indeed most commutes are to downtown. However, commuting was already taken care of in the first stage, and there is no need to account for it *again*; instead, I am accounting for the *amenity* effect of living closer to downtown, which is distinct from

It is difficult to gauge the quality of individual schools, so instead I use educational attainment (specifically the percentage of residents over the age of 25 with an Associate’s degree or higher) as an instrument for quality of nearby schools, as highly-educated parents are more likely to choose to live in areas where it is easier for their children to attend good schools.¹⁹

I assume housing age, distance to Lake Michigan, and travel time to downtown to have exponential functional forms (that is, residential amenity decays exponentially as any of these quantities increase). I also assume (log) amenity to is related logarithmically to vacancy rate, greenspace, commercial area, and average education level. So the control term in (12) and (13) can be more explicitly written as

$$\begin{aligned}\beta \mathbf{X}_i = & \beta_1 age_i + \beta_2 \log(vacancy_i) + \beta_3 lakedist_i + \beta_4 downtown_i \\ & + \beta_5 \log(greenspace_i) + \beta_6 \log(commercial_i) + \beta_7 \log(education_i),\end{aligned}$$

where the first four coefficients are expected to be negative, while the last three are likely positive.

4.2.3 Further Empirical Considerations

Collateral effects My analysis assumes that a tract’s amenity is affected by the crime rate *in that tract* only. In reality, there is likely to be a “collateral” effect, where the amenity of a tract is also influenced by crime rates in neighboring tracts. In other words, we would rewrite (2) as

$$B_i = \bar{B}_i c_i^{-\gamma} \left(\sum_{s=1}^S e^{-\eta t_{is}} c_s K_s \right)^{-\hat{\gamma}},$$

for some $\eta, \hat{\gamma} > 0$. Namely, the effect of neighboring tracts decays exponentially as travel times to those tracts increase; the effect of an individual tract i is also weighted by its

(although clearly related to) commuting costs.

¹⁹Of course, these parents are also more likely to avoid high-crime areas, so there might be significant collinearity.

size K_i .²⁰ While accounting for this collateral effect could influence the estimated effect of crime, it also introduces a number of new variables that complicate the analysis. For that reason I disregard collateral effects, although this might be a worthwhile topic for future research.

Other crimes My analysis only considers violent and property crimes, which is not to suggest that other crimes do not have a deleterious effect on residential amenity. A number of crimes that do not directly cause damage to person or property—like prostitution, illegal gambling, drug use and sale, and petty vandalism (such as graffiti)—can also have a noticeable effect on amenity. However, these crimes are much more likely to go unreported, and they are not as significant as violent or property crimes; therefore, I think it is reasonable to disregard these crimes for my analysis.

5 Results

5.1 Residential Amenities

A fixed effects regression on the linear equation (11) yields the results in Table 1 in the attached document. The estimated amenities are shown in Fig. 4 in the Appendix. For the four different specifications, I use two sets of residential floorprice data (median and mean rent per room) and two measures of residential capacity (residential/mixed-use zoning area and non-green area). The estimated value of θ is consistently large and varies significantly across specifications, but the estimated $\theta\kappa$ hovers around 0.05 for all specifications. This means that, all else equal, a one-minute increase in commuting time decreases the commuting flow by 5%. This is similar to the value obtained in ARSW; the authors found that, for the city of Berlin, the commuting flow decreases by 7% for every one-minute increase in travel time.²¹ ARSW estimated θ to be 6.83, nearly half the value I obtained in specification (1). However, $\theta = 11.02$ is still broadly in line with the range of

²⁰A collateral effect might also exist for other neighborhood characteristics, like vacancy rate and green space.

²¹This discrepancy would make sense if Americans have longer commutes, on average, than Germans. Some surveys suggest this is true while others disagree (OECD (2015)).

estimates for the Fréchet shape parameter for international trade flows.²² Because larger values of θ will reduce variation in amenity B_i , I will henceforth use only the calculated amenities from specification (1).

The regression yields amenities for 741 tracts (as we've excluded some of the tracts, as mentioned above). I normalize all amenities to be no greater than 1. The smallest amenity is 0.37, and the distribution is heavily concentrated in the range $[0.5, 0.6]$ (475 of the values fall in this range). The significance of this distribution is explored in the next section.

5.2 Crime

Tables 2 and 3 (in the attached document) show the results of computing the linear regressions in (12) and (13), respectively, using different crime rates.²³ The first column in both tables shows the effect of the combined violent and property crime rate, without controls, while the second column includes all controls. Adding the controls has almost no effect on the crime coefficient, which suggests that the controls are largely orthogonal to the crime rate. The remaining six columns show the results of regressing (with controls) on different crime rates: violent crime, property crime, violent and property crime, homicides, homicides and non-homicide violent crime, and homicides, non-homicide violent crime, and property crime. While column 4 suggests that property crime rate is a significant determinant of amenity, the effect disappears when the regression includes violent crime, as in columns 5 and 8. Furthermore, the effect of violent crime seems to be dominated by non-homicidal crimes. Columns 7 and 8 in Table 2 suggest that the homicide rate might also have a distinguishable effect, but the logarithmic specification forces us to ignore the 242 tracts which reported no homicides during the period of interest. The results of the log-linear regression in Table 3 suggest that the homicide rate is not a good predictor of amenity. And, in fact, the high standard error suggests that the homicide rate is strongly collinear with the non-homicide violent crime rate. Regressing homicide rate on non-homicide violent crime rate shows that the two rates have a correlation of

²²According to Eaton and Kortum (2002), an acceptable range is from 3.60 to 12.86, with 8.28 being preferred.

²³In Table 3, the coefficients are given for crime rates in thousands of incidents (per 100,000).

0.834.

Interestingly, every regression suggests that amenity actually *increases* with vacancy rate, which contradicts the intuition from earlier. Perhaps vacancy rate is not necessarily a good instrument for urban blight, as a number of high-vacancy neighborhoods tend to have high amenities (many parts of downtown, for instance, have high vacancy rates, as apartments there probably have high turnover). A slightly less interesting result is that proximity to Lake Michigan does not—in most of the regressions—have a significant effect on amenity (but travel time to downtown very much does).

The relatively small values of the crime coefficients may come as somewhat of a surprise. Table 2 suggests that a doubling of the violent crime rate will only decrease amenity by about 3.9%; from Table 3, we see that an increase in the violent crime rate of 1000 incidents (per 100,000 residents) will decrease amenity by roughly 3.8%. However, upon examining the values of the amenities calculated in the first stage, these results should not be surprising. 475 tracts (out of 741 for which amenity was calculated) have amenities between 0.5 and 0.6, so even a small decrease in amenity in absolute terms can translate to a very significant drop in relative terms. The shape parameter θ also plays an important role in determining how people respond to changes in amenity. The high estimated value of θ found in the previous part suggests that preferences are actually fairly homogeneous (i.e., the stochastic term $z_{ij}(\omega)$ deviates little from the mean), so even small differences in amenity can have a significant impact on residential patterns, as people are largely affected by amenity in the same way. All this is to say that while residential amenity has a concrete definition in the model, it doesn't mean the same thing as our own intuitions would lead us to believe. (Although very subjective, our intuition probably tends to exaggerate the amenities.) But importantly, the objective amenity in the model successfully captures agents' preferences and the consequences of these preferences on urban residential patterns.

6 Conclusion

In this paper I used a novel model of urban geography to estimate residential amenities for census tracts in the city of Chicago. Although the estimation procedure (which uses a fixed effects regression) introduces some noise, I was able to detect a crime effect on amenity when I regressed amenity on violent and property crime rates, as well as controls. The effect of crime was perhaps smaller than expected, but when considering the objective amenity (and the distribution of its values) used in the model, it was not unreasonable. Therefore, I was able to verify both the empirical tractability of the model, as well as the hypothesis that crime rate has a significant effect on residential amenity. Furthermore, I addressed several empirical considerations—such as accounting for differences in location sizes—that might be helpful for further work using gravity models in urban geography.

Further work can apply the general equilibrium formulation of the model to test counterfactuals; that is, to see how changes in the crime rate affect residential and commuting patterns for the specific case of Chicago (although this effect was demonstrated for the simple toy model earlier). It would also be worthwhile comparing the results for Chicago with those for other large cities (like New York or Los Angeles), as well as smaller ones (like Boston or St. Louis).

Since most American metro areas extend well beyond the city limits proper, a more thorough approach would require considering commutes for all pairs of locations within the metro area. From the perspective of economic geography, city boundaries are quite meaningless, and many of them were drawn over a century ago. However, it is important to keep in mind that there might be shortcomings to including both urban and suburban areas in a single model, as they tend to have quite different characteristics (for instance, land prices rather than floor prices would dominate in less densely populated areas).

Nevertheless, despite making a number of assumptions and using a relatively constrained data set, I was able to analyze the micro effects of urban crime in a way that casts light on the impact of crime beyond the damage it causes directly to persons and property. It is important to note that this is only one of many ways to think about crime, but it is one that shouldn't escape consideration when cities consider zoning and policing

policies.

7 Appendix: Figures

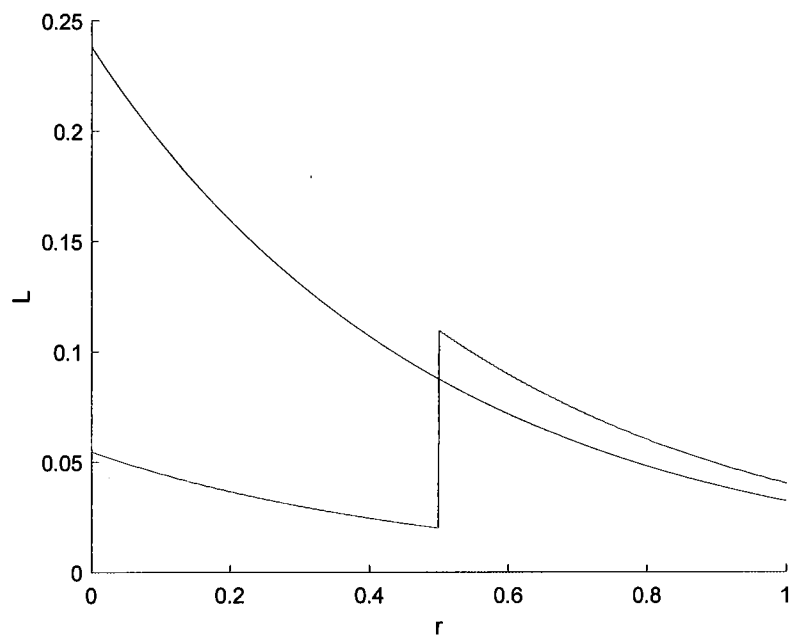


Figure 1: The blue curve signifies labor density in the case of constant amenity across the city. The red curve signifies labor density when amenity declines for $r < 1/2$, but rises elsewhere. More people are brought closer to the outside of the city, where amenity is higher but commutes are longer.



Figure 2: *Left:* Median rents per room, by tract. (Darker blue signifies higher rent; lighter green signifies lower.) *Right:* Average commuting time by tract, for residents who work in the city of Chicago. (Blue signifies shorter commutes.)



Figure 3: *Left:* Violent crime rates by tract. (Red signifies higher rates.) *Right:* Property crime rates by tract. We can see that violent crime is more concentrated in the west and south of the city, while property crime is more diffuse.

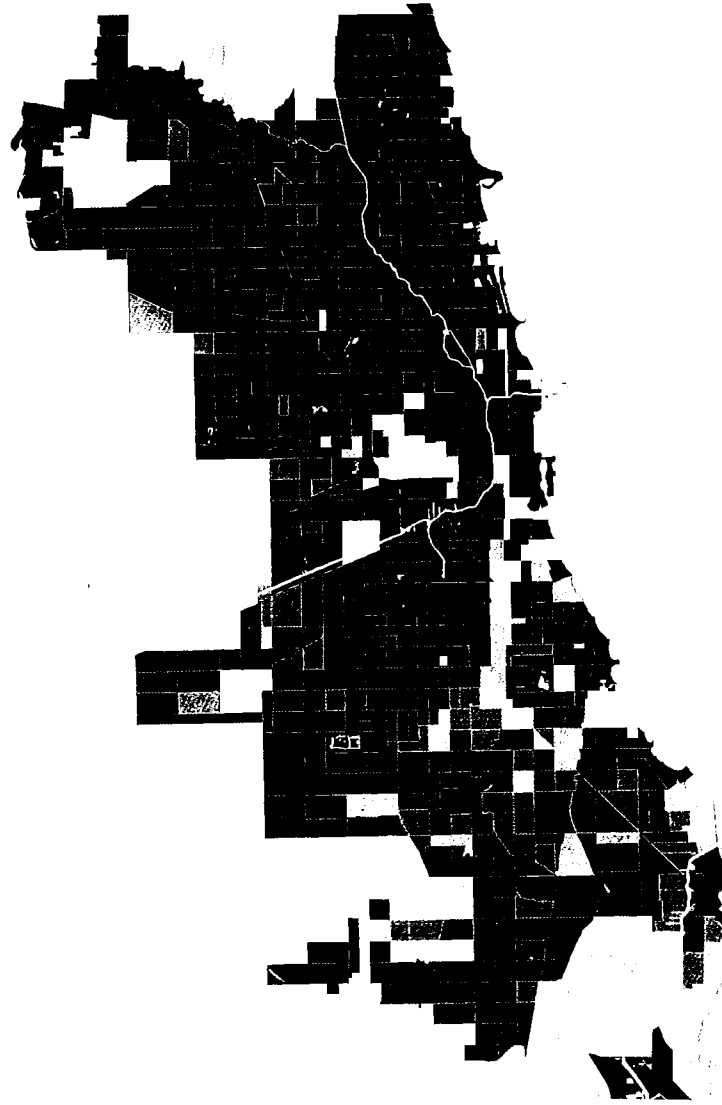


Figure 4: Estimated residential amenities, by tract. Dark blue signifies higher amenities. Gray tracts were excluded from the regression due to small populations or small residential areas.

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Table 1: Commuting Flows Regressions

	(1) Median rent per room, residential area	(2) Median rent per room, non-green area	(3) Mean rent per room, residential area	(4) Mean rent per room, non-green area
θ	11.02*** (1.39)	19.47*** (1.40)	18.03*** (2.27)	31.86*** (2.29)
κ	0.0046*** (0.0006)	0.0026*** (0.0002)	0.0028*** (0.0004)	0.0016*** (0.0001)
R^2_{adj}	0.3569	0.3993	0.3569	0.3993
N	295,278	305,639	295,278	305,639

Table 2: Crime Regressions, log-log model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(violent and property)	-0.0379*** (0.0056)	-0.0363*** (0.0053)						
Log(violent)			-0.0392*** (0.0048)		-0.0389*** (0.0053)			
Log(homicide)						-0.0350*** (0.0043)	-0.0140** (0.0064)	-0.0138** (0.0064)
Log(non-homicide violent)							-0.0351*** (0.0080)	-0.0306*** (0.0085)
Log(property)				-0.0132*** (0.0039)	-0.0006 (0.0041)			-0.0080 (0.0050)
Housing age		-0.0023*** (0.0003)	-0.0024*** (0.0003)	-0.0021*** (0.0003)	-0.0024*** (0.0003)	-0.0015*** (0.0004)	-0.0020*** (0.0004)	-0.0020*** (0.0004)
Log(vacancy rate)		0.0478*** (0.0093)	0.0559*** (0.0094)	0.0228*** (0.0085)	0.0558*** (0.0094)	0.0617*** (0.0100)	0.0783*** (0.0111)	0.0779*** (0.0111)
Distance to lake		-0.0008 (0.0009)	-0.0011 (0.0009)	-0.0005 (0.0010)	-0.0011** (0.0009)	0.0002 (0.0010)	0.0003 (0.0010)	0.0002 (0.0010)
Time to downtown		-0.0041*** (0.0007)	-0.0038*** (0.0007)	-0.0043*** (0.0007)	-0.0038*** (0.0007)	-0.0019** (0.0008)	-0.0023*** (0.0008)	-0.0024*** (0.0008)
Log(green space)		0.0117** (0.0047)	0.0116** (0.0046)	0.0113** (0.0048)	0.0116** (0.0046)	0.0038 (0.0051)	0.0045 (0.0051)	0.0044 (0.0051)
Log(commercial)		0.0700*** (0.0101)	0.0748*** (0.0101)	0.0663*** (0.0103)	0.0746*** (0.0100)	0.0682*** (0.0112)	0.0757*** (0.0114)	0.0744*** (0.0114)
Log(education)		0.0637*** (0.0072)	0.0552*** (0.0073)	0.0749*** (0.0072)	0.0554*** (0.0074)	0.0472*** (0.0082)	0.0472*** (0.0082)	0.0488*** (0.0082)
R^2_{adj}	0.0565	0.5598	0.5592	0.5273	0.5592	0.4656	0.4637	0.4653
N	741	741	741	741	741	529	529	529

Table 3: Crime Regressions, log-linear model

[illegible]