CRIMINAL ACTIVITY AND ACCESS TO RAIL TRANSIT: AN EXAMINATION OF THE RELATIONSHIP IN CHICAGO

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ABSTRACT

The relationship between access to transit and crime is vague and complex, but also clearly rooted in both intuition and economic theories of crime. Parsing that relationship could lead to significant breakthroughs in the effectiveness of urban and suburban policy. This paper seeks to develop a more firm understanding of that relationship through an analysis of crime near "L" Stops in Chicago, Ill.

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Introduction

The relationship between metropolitan transit systems and criminal activity is tense, but also vague and scarcely researched. Voices on both sides of urban policy debates frequently reference claims to one end or another, despite that little empirical evidence exists in the field to support any political agenda. Two years ago in Troy, Michigan, for instance, local leaders nixed plans for an $8.5 million stimulus funded transit center after members of the city council referred to public transit systems as "mugger movers".[1] Conversely, city planners frequently cite claims that transit systems reduce crimes in order to encourage transit-oriented development. But although the political motivations may be questionable, the emotions being stoked are grounded in a legitimate intuition. It is clear that some complex relationship exists between urban transit systems and criminal activity, but just what that relationship may be is difficult to qualify or quantify.

A significant amount of research has been conducted on the broader field of the economic implications of urban transit systems, addressing more obvious questions of property values and urban development. These relationships have proven dynamic, influencing different environments in different ways, with varying levels of severity. That said, these myriad effects have also proven to be quantifiable. (Mohammad, 2013) Although difficult, they are not out of the reach of urban, or more generally, empirical economics.

Urban transit systems enhance mobility and access to and from commercial areas, and thus represent a form of economic investment. They are routinely implemented as a system of addressing the significant externalities of traffic and urban sprawl. At the same time, transit

[1] Wattrick, Jeff. "Michigan Ann Arbor Bay City Detroit Flint Grand Rapids Jackson Kalamazoo Lansing Muskegon Saginaw All Michigan." *MLive.com*. University of Michigan, n.d. Web. 23 Mar. 2014.

systems claim externalities of their own, bringing noise, blight, and potentially criminals.

The implications of a clearer understanding of this relationship are vast, potentially enabling the transformation of urban and suburban neighborhoods, as well as the environment and congestion levels of metropolitan areas at large. Suburban fears of a link between transit and crime impede mobility into the city center and necessitate – especially in America – a ubiquitous over-reliance on cars. Likewise, urban concerns redirect investment funds and influence policing decisions, thereby affecting segregation and crime levels indirectly. Clarity on this link could serve as a guide to these myriad political concerns.

Transit systems can be thought of as influencing crime patterns in three ways. Most obviously, transit centers serve as a hub of activity, a location with a "high land use intensity" level (Angel, 1968). According to a general theory of crime, dependent upon population and population density, increases in land use intensity should increase criminal activity simply by increasing the numbers of potential victims and potential criminals in close proximity to one another. This is more or less accepted as a reality of any urban activity hub, and – with regard to transit centers specifically – has been effectively confirmed. (Block & Block, 2000)

Less obviously, but perhaps of greater concern, is that transit systems may actually be "mugger movers", improving mobility for commuters and travelers, but also for criminals. This presents a more pressing concern in that it affects whole communities accessible by transit, and affects more distant suburban communities. The extent to which this has been researched is unclear, as most of the existing literature simply addresses the crime-transit relationship from an econometric perspective, failing to distinguish between these two frameworks. That said, some have addressed it directly, and evidence is mixed.

Lastly, considering crime as a function of neighborhood characteristics compels us to consider the indirect effects of transit-oriented development, or transit externalities, on crime.

This relationship is typically considered indirectly, through meta-analyses and planning guides that take multiple research questions into consideration simultaneously.

This paper seeks to complement the relatively thin existing literature on the link between transit and urban rail systems by differentiating between the “land use intensity” and criminal mobilization theories and subsequently testing a unified theory using spatial econometric techniques. Urban heavy rail systems are chosen as a simplifying measure, given the relative scarcity of stations, and the broader, more enduring impact of their existence than – for instance – bus systems. They are also unique from bus and even light rail transit in that they are completely removed from traffic conditions, enhancing their effect on mobility. Chicago’s elevated rail system, the “L”, is chosen specifically because of the quality of Chicago’s data resources.

Background and Literature Review

Although little empirical research has been done on this topic directly, there is no lack of literature generally concerning the determinants of crime, or the impact of transit. As pointed out in Billings, Leland, Swindle (2011), a great deal of non-economic research has been done on perceptions of the crime-transit link. For instance, Ross (1985) found that crime was the 2nd biggest transit implementation concern, after temporary construction-related traffic congestion. Likewise, studies of auxiliary concepts, like impacts on property rates, economic activity, or congestion, are numerous. A meta-analysis of the impact of urban transit systems on land and property values, with a thorough discussion of related externalities, was published last January (Mohammad, 2013), and provided an invaluable guide for considering all possible effects of transit.

Six studies have been conducted examining the relationship between crime and transit, five of which employ econometric techniques. The studies don't approach the issue the same way, however.

The simplest (Block & Davis, 1996) and its updated version (Block & Block, 2000), survey the issue using the land use intensity model mentioned in the introduction and first presented in an analysis by Shlomo Angel (1968). This model essentially treats crime as a function of land use intensity, increasing in the density of potential victims before declining in the density of potential witnesses. Block & Block's analysis – shown left - all but confirmed this theory's application to transit hubs, finding that criminal activity peaked 1.5 -2 blocks from stations.

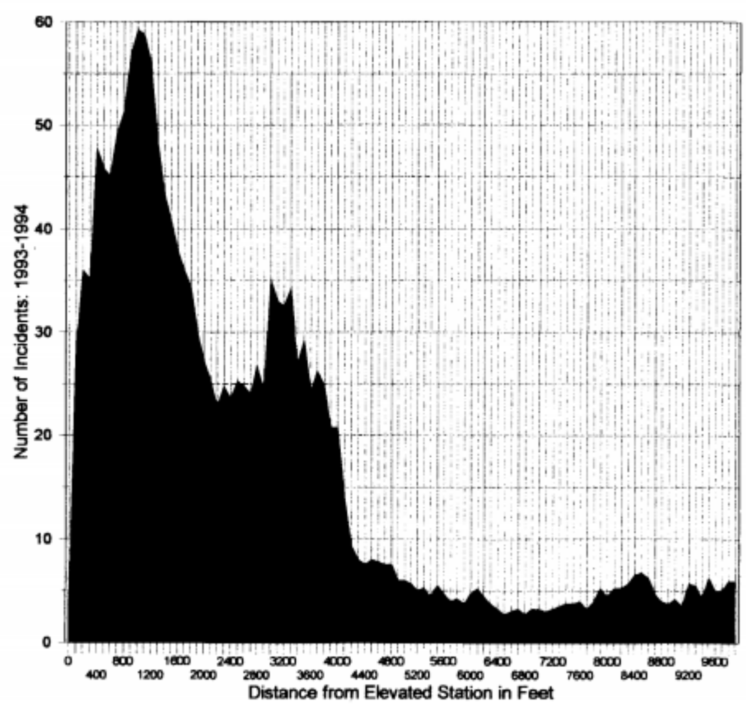

Figure 1 Chicago's Northeast Side, 1993-1994: Distance from Elevated Station by Number of Incident; Source: Block & Block (2000

Four of the five remaining studies approach the question with time series, or quasi-experimental, analyses, with mixed results. Poister (1996) and Plano (1993) both found some evidence, if ultimately inconclusive, for moderate increases in criminal activity following the opening of Atlanta (MARTA) and Baltimore Metro stations, respectively. Poister's analysis also indicated a subsequent drop in crime after the community had acclimated to the station, roughly two years later. Billings, Leland, and Swindle (2011), on the other hand, employed a quasi-experimental model to analyze the impacts of both the announcement of a transit stop as well as the construction, finding that crime may actually decrease with the implementation of transit services. Liggett, Loukaitou-Sideris, and Iseki (2002) employed time series data and localized hot spot analysis to similar conclusions, finding that there is no conclusive relationship, if a possible decrease in crime.

Only Ihlanfeldt (2003) attempted to estimate a linear relationship between access to transit and crime measures. His estimates demonstrate a small but statistically significant relationship. More importantly, however, the Ihlanfeldt study highlighted the relevance of community characteristics, by noting that an additional station can increase crime in an urban setting while decreasing it in a suburban setting. Despite building his empirical model from a uniquely comprehensive spatial economic model of crime, he failed to distinguish between mobility generated crime measures and "land use intensity" caused fluxuations. In this regard, his estimates likely demonstrate a positive bias on the transit access coefficients.

Ultimately, the current answer is that there is no clear link. And, quite likely, there will never be a single concise answer to this problem. Community characteristics may be too relevant to simply control for, and crime trends may be too vague to separate from the transit effects. Nevertheless, this paper seeks to clarify the relationship by building primarily on the Ihlanfeldt study, using different data sets (and a different geographical region), updated neighborhood controls, and factoring in the effects of Block & Block's land use intensity model.

Conceptual Framework

The conceptual framework of this study can be broken into two parts: Angel's land use intensity model of crime, and Ihlanfeldt's spatial economic model of crime.

Land Use Intensity

Crime was originally posited as a function of land use intensity by Shlomo Angel (1968), and summarized by Susan Wilcox (1973):

> "As the intensity of use increases, the number of potential victims available increases sufficiently to attract the attention of potential offenders, but people are not sufficiently numerous to provide witnesses. This situation is called the "critical intensity zone," [Zone 2] and is the situation in which most street crimes are theorized to take place. When the intensity of use is very high [Zone 3], the level of activity is high enough to create a number of witnesses adequate to deter the potential offender."

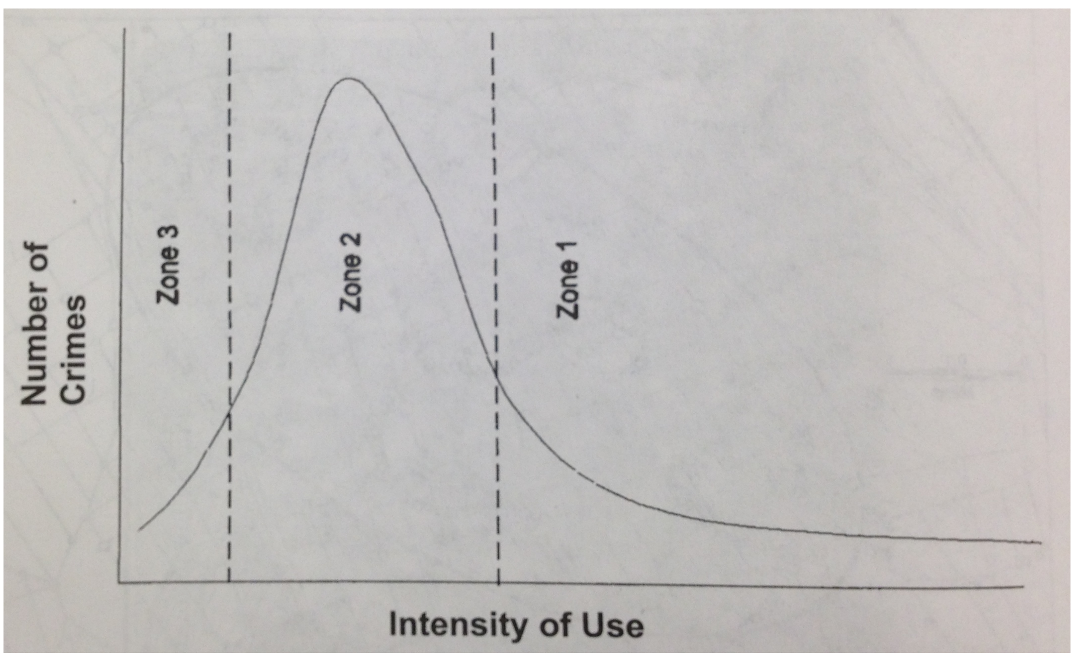

Figure 2 - Crimes as a function of intensity of land use.

Conducting a similar analysis using a crime density measure, as opposed to the raw incident aggregate used in Block & Block, the updated "Zone 2" peak for distance from Chicago "L" stations is roughly 25 meters, significantly closer than the estimates in the Block study. These estimates are shown in Figure 3, below.

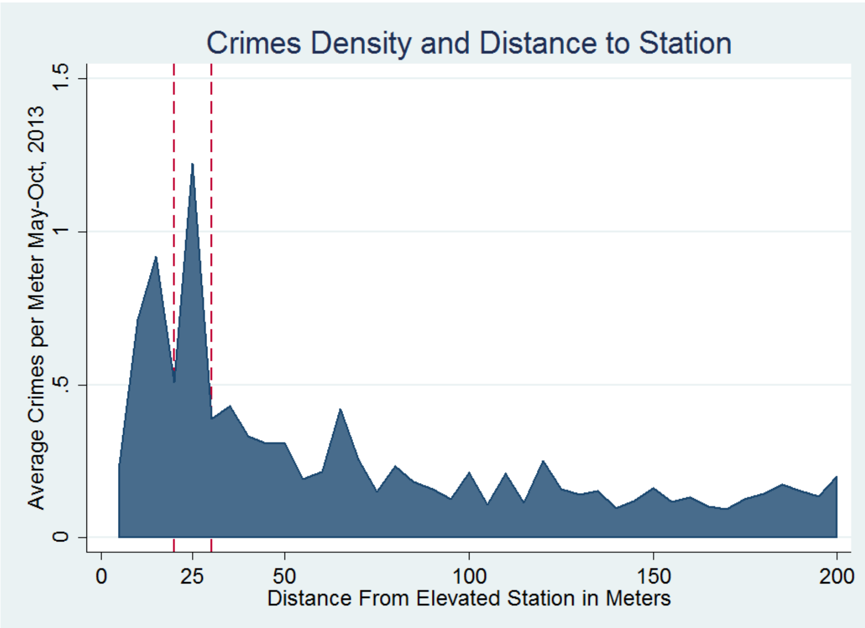

Figure 3 - Crime density and distance to station. Theoretical "Zone 2" designated by dashed red line.

As such, the dependent variable in the regression model omits crimes that occur within 30 meters of transit station. This allows the empirical model to delineate the influence of the effectively proven land-use intensity model from the spatial economic model, dependent primarily on mobility.

Spatial Economic Model of Crime

The probability of resident (*R*) committing a crime in home neighborhood (*H*), as opposed to an outside neighborhood (*O*) is equal to the marginal probability that *R* is a criminal (*C*) times the conditional probability that R will commit the crime in neighborhood *H*.

$$P_H^R = P(C) * P(H|C)$$

The first term here, the marginal probability that *R* will commit a crime is explained in the standard aspatial crime model (Becker, 1968), wherein the expected net utility (π) is equal to the payoff (ω) net costs (c) and the probability of apprehension (ρ) times the penalty if apprehended (x). Of course, this model makes most sense in the context of property crimes, but it can be applied elsewhere if we think of ω in the more conceptual sense of marginal utillity.

$$\pi = \omega - c - \rho x$$

We can add a spatial dimension to this model, by factoring mobility into both costs and probability of apprehension. Since we assume average costs are equal across geographies, we can define costs as equal to access (a_O) to a target neighborhood (O), and hold penalties constant across geographies.

$$\pi_H = \omega_H - \rho_H x$$

$$\pi_O = \omega_O - \rho_O x - a_O$$

Putting these concepts together, we can state mathematically that the potential criminal will maximize net utility by choosing whether committing a crime in either H or O provides greater utility than the alternative legal activity. The right side of this inequality is defined as expected pay from legal activity (e) net journey to work costs (j) plus some theoretical psychological benefit from abstaining from criminal activity (g).

$$max(\pi_H | \pi_o) > e - j + g$$

We can define a and j as functions of availability of transit (T) and distance to either the crime target or place of work ($D_{\langle C|W \rangle}$). Collecting these terms together we can define the total probability of crime in neighborhood H:

$$P_H = f(\omega_{\langle H|O \rangle},\ \rho_{\langle H|O \rangle}, D_{\langle C|W \rangle}, T, e)$$

If, instead of thinking of the $\langle H|O \rangle$ dichotomy as embodying a choice for resident R to either stay and commit the crime at home or to leave and commit it elsewhere, we think of it as the joint probabilities that a resident of neighborhood H (R_H) and a resident of an outside neighborhood (R_O) both choose to commit their crimes in neighborhood H, we see that P_H is total probability of crime in *H.*

Interpreting this probability, we can assume that the magnitude of ρ is inversely related to access to transit. Since *j* and a are both functions of *T*, however, the sign on T remains ambiguous. Ultimately, this model is merely illustrative. Crime rates remain difficult to decompose entirely, as recent links between variables as diverse as usage of leaded paint and gasoline or abortion rates have come to light. As such, the best this model can do is provide a framework for empirical analysis, granting us insight into the correlations we may establish.

Data and Empirical Framework

Employing a simple least squares regression model, we attempt to identify a linear relationship between a census tract's access to public transit and its crime levels. Initially, we intended to capitalize on a line closure on Chicago's south side that took place from May 2013 through October 2013 in order to contribute time sensitive variation into the model. It quickly became clear, however, that due to the nearly universal decline in Chicago's 2013 crime rate, this variation would be misleading. As such, the model relies entirely on cross sectional data to determine a relationship. The simple model is given by:

$$Crime_{ij} = \beta_0 + \beta_1 Access_i + \delta X_i + \varepsilon_i$$

The primary dependent variable, $Crime_{ij}$, is given by crimes (less crimes within 30 meters of a station) – of categorical type *j* – per square meter for tract *i.* Crime density, as opposed to a per-population crime rate, is used because the theory predicts a spatial relationship, positing crime as a function of mobility between populations. Moreover, many crime targets are non-residential in nature, and thus affect crime density more consistently across tracts than crime rate measures. These theoretical motivations are also confirmed by research (Bowes & Ihlanfeldt, 2001) that found crime density measures to have a significantly larger effect on public perceptions of crime, and thus, property values.

As a secondary dependent variable, crime {Getis-Ord Gi*} hot spot analyses were conducted using ArcGIS software. In conducting this analysis, incident points within 10 meters of one another were snapped together, using the integrate tool. They were then collected into weighted point data. The hot spot tool interprets the spatial relationship of these weighted data, analyzing clusters of weighted points and assigning each a hot spot significance value, or a "z-score". The "z-score" is the same z-score as in a standard statistical significance test. These analyses are useful only if the spatial relationship is appropriately conceptualized. A relatively narrow distance band (10 meters) was employed in an effort to capture variation at a local level. Visualizations of these analyses illustrate their limitations, as statistically significant "hot spots" cover wide swaths of land, and are thus unlikely to be particularly useful for determining a causal relationship at a local level. Still, they provide a useful visualization of crime trends

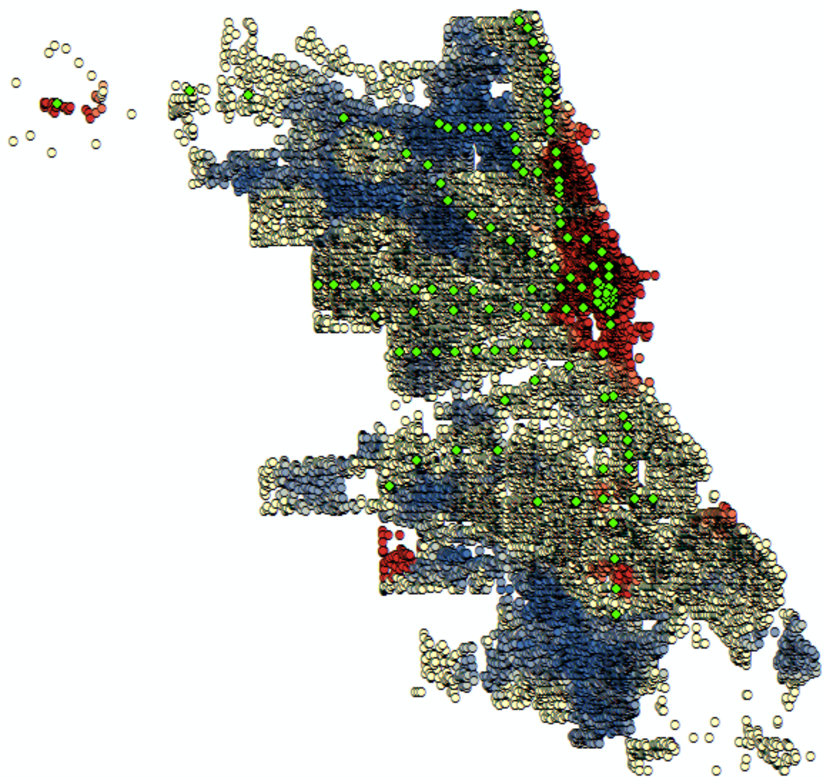

Figure 4 - Getis-Ord Gi Hot Spot Analysis of Property crime in Chicago. Red represents high Z scores.*

in the Chicago area. These analyses, mapped against L stops, are shown here.

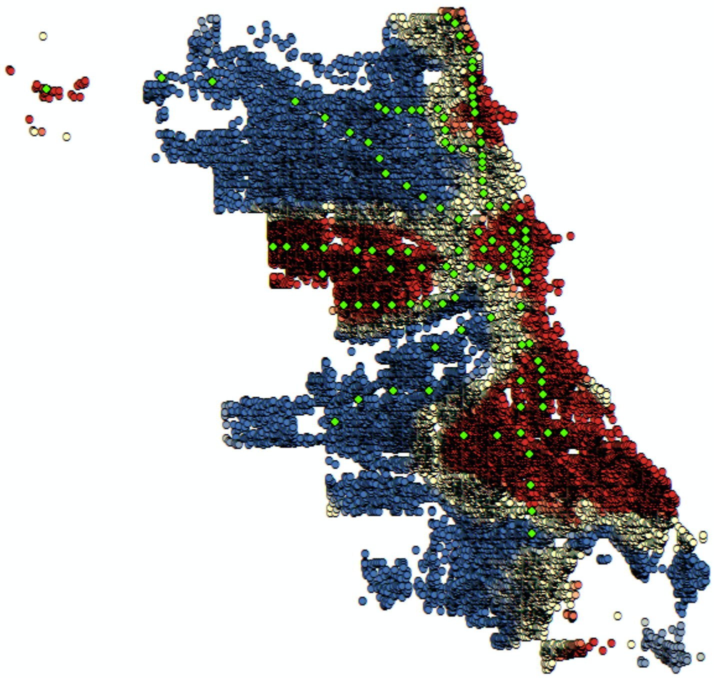

Figure 5 - Getis-Ord Gi Hot Spot Analysis for violent crime in Chicago.*

Crime data was accessed through the City of Chicago Data Portal's dataset titled "Crimes – 2001 to Present".[1] Crimes are categorized, by FBI Universal Crime Reporting code as either "Violent" (Assault, Battery, and Homocide) or "Property" (Burglary, Motor Vehicle Theft, Theft, and Robbery).

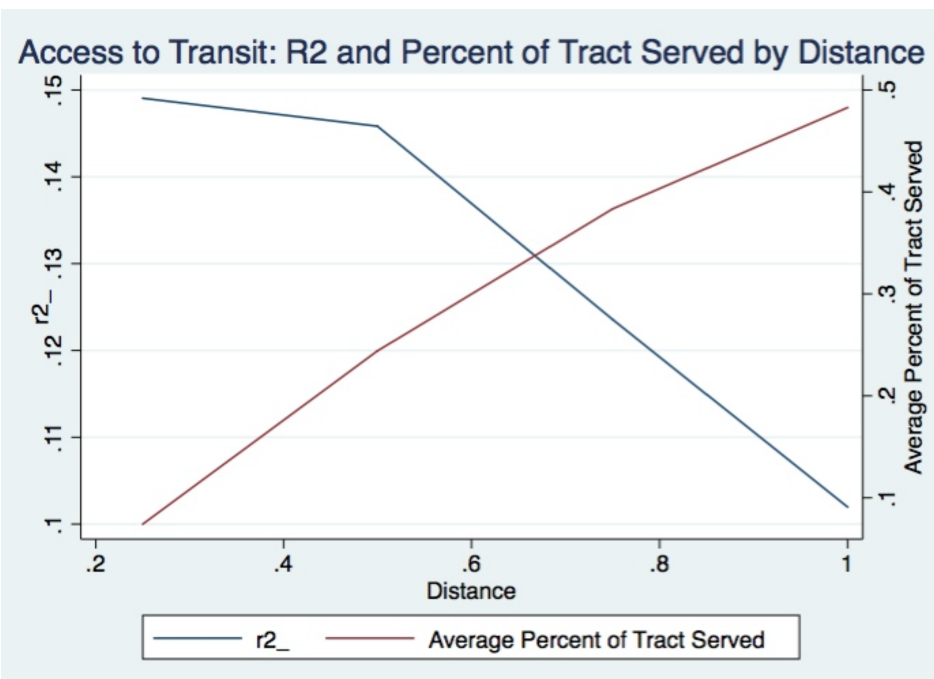

Figure 6 Explanatory power of crime density on transit coverage regressions and average percent of tract served by distance.

L Stops were geocoded using Chicago Transit Authority data, also from the Chicago Data Portal website. *Access* is defined as the percent of tract *i* that is served by elevated rail transit. To choose the most significant measure of service to a tract, crime was regressed on the percent of tract within a set of radial distances from "L" stops. As shown in the Figure 6, the quarter mile band demonstrated the greatest explanatory power.

A full set of neighborhood characteristics are included in order to account for various aspects of the conceptual framework. Table 1 details this list, along with descriptions, sources and links to the conceptual model.

Table 1 - Explanatory variables

Variable	Link to Theory	Description	Source
access	T, j, a, ρ	Percent of tract "served" by L station	Chicago Transit Authority
distpoor	$D_{\langle c \rangle}, a$	"Distance to poverty" score increases with proximity to poverty.	ACS 2012 5yr (S1901)
jobaccess	$D_{\langle w \rangle}$, □, e	Job access score increases with proximity to job growth in sectors appropriate for males age 16-24	CPS AAT Industry Estimates, IDES Employment Estimates, ACS 2012 5yr (S2403)
commute	j	Average commute time for workers 16 and older	ACS 2012 5yr (S0801)
ethnonwhite	*general*	Percent of residents of minority ethnicity	ACS 2012 5yr (DP05)
income_mean	ω	Mean income of tract	ACS 2012 5yr (S1901)
male1624	$D_{\langle c \rangle}$	Percent of tract that is male and 16 to 24 yrs old	ACS 2012 5yr (S2301)
manufacturing	j, a	Percent of tract employed in manufacturing	ACS 2012 5yr (S2403)
noHS	*general*	Percent of tract without a high school diploma	ACS 2012 5yr (S1501)
police	□	Number of calls per officer by police district	Chicago's Office of Emergency Management[2]
pop_density	*general*	Population density of tract	ACS 2012 5yr (S2301)
retail	j, a	Percent of tract employed in retail occupations	ACS 2012 5yr (S2403)
stayers	*general*	Percent of residents who have occupied their home for more than 3 years	ACS 2012 5yr (DP04)

[2] The City of Chicago's Office of Emergency Management provided 911 data in response to the ACLU's FOIA request. The Chicago News Cooperative published the number of police officers per district based on a police source. *See* Dan Mihalopoulos and Hunter Clauss, "In High-Crime Areas, Still Too Few Police," Chicago News Cooperative (Oct. 21, 2011).

Generally, these data are pulled directly from the census or other datasets and used as is.[3] *Distpoor* and *jobaccess* are*,* however, more complicated than that. Both are based on variables of the same name in Ihlanfeldt (2002), but differ in their construction. In attempting to quantify "distance to poverty", we generated a score that is higher for tracts with greater proximity to poor tracts. The variable is a weighted sum of the inverse of the distance between a given tract and each other tract, where the weight is the proportion of the "near" tract that is impoverished and the relative size of each tract. It is given by the equation:

$$distpoor_i = \sum_{j=1}^{j} p_j \times s_j \times \frac{1000}{d_{ij}}$$

where s_j is the relative size of tract *j,* p_j represents the percent of tract *j* living in relative poverty, and d_{ij} is the distance from tract *i* to tract *j.* "Relative poverty" is specified as the percent of the tract earning less than $24,999 annually, chosen because it represents 125% of the poverty line in Chicago for an average household of three (2.67 is the average household size in Chicago) and rounding up provided greater explanatory power.

Jobaccess attempts to quantify the availability of jobs to potential criminals by generating a weighted sum of inverse of distance to job growth in appropriate sectors for the target demographic of criminals, males age 16 to 24. It is given by the equation:

$$jobaccess_i = \sum_{j=1}^{j} \sum_{k=1}^{k} g_{kj} \times K_k \times t_k \times \frac{1000}{d_{ij}}$$

[3] Last minute complications rendered roughly a third of tracts without neighborhood controls. The missing values were spread out in an apparently random fashion, and more than 560 tracts remain with a full set of controls. *Distpoor and jobaccess* were unaffected by the data loss, except for that the K variable in *jobaccess* was impaired and, thus, averaged across missing tracks spatially.

where g_{kj} is the year on year growth of industry k in tract j, K_k is the proportion of total employment industry k represents within tract j, t_k is the national proportion of employees of industry k in the target criminal demographic, and d_{ij} is the distance between tract i and j. Yearly industry employment estimates are not available through the Census, whose ACS 1 year estimates are not sufficiently detailed. Thus, they had to be accessed via the Illinois Department of Employment Security "Where Workers Work" table at the zip code level and averaged across tracts where a tract contained multiple zip codes. Likewise, the demographic makeup of industries is only available through the BLS CPS Annual Average Table 14 at a national level. The ACS did allow us accurate tract level estimates for *K*, however. For both *jobaccess* and *distpoor*, ArcGIS was used to create a dataset of distances between each L station, as well as join and average all of the demographic data across census tracts. In the empirical analysis, *distpoor* and *jobaccess* were both squared and interacted with access, accounting for non-linear relationships between these variables.

Results

Across the board, the results demonstrate a statistically significant relationship between access to transit and crime, especially when interacted with our spatially dependent variables, *distpoor* and *jobaccess.* The relationships imply that transit stations do increase criminal activity. Despite the abundance of neighborhood control variables, however, our models only explain a little above 50% of crime. Given that we know tracts with access to transit have higher crime rates than tracts without – due at least in part to reasons that have little to do with mobility across tracts – we cannot rule out possible

Table 2 - Regression Estimates

VARIABLES	(1) allcrime_dens	(2) allcrime_z	(3) prop_dens	(4) property_z	(5) violent_dens	(6) violent_z
access	0.886***	28.05	0.322***	141.6***	0.188***	137.4***
	(0.145)	(24.36)	(0.0637)	(35.96)	(0.0375)	(44.39)
*access*distpo*	-1.461***	-49.12	-0.550***	-240.0***	-0.300***	-233.5***
-or	(0.220)	(37.00)	(0.0967)	(54.62)	(0.0570)	(67.42)
*access*distpo*	0.569***	15.99	0.215***	86.32***	0.114***	82.38***
-or^2	(0.0828)	(13.92)	(0.0364)	(20.55)	(0.0214)	(25.37)
*access*jobacc*	0.127***	22.20***	0.0699***	54.60***	0.0254***	63.58***
-ess	(0.0251)	(4.229)	(0.0110)	(6.242)	(0.00651)	(7.705)
*access*jobacc*	-0.434***	-73.60***	-0.230***	-177.6***	-0.0852***	-209.4***
-ess^2	(0.0845)	(14.21)	(0.0371)	(20.97)	(0.0219)	(25.89)
distpoor	-0.0195	-11.01***	0.0123	8.953*	-0.0109**	2.641
	(0.0192)	(3.228)	(0.00843)	(4.764)	(0.00497)	(5.882)
dist2	0.0186**	5.510***	-0.00117	-4.099**	0.00713***	-1.882
	(0.00805)	(1.354)	(0.00354)	(1.998)	(0.00208)	(2.466)
jobaccess	-0.00254	-0.566	-0.00233**	0.412	-0.000847	1.230
	(0.00265)	(0.445)	(0.00116)	(0.657)	(0.000686)	(0.811)
job2	0.00532	1.846	0.00623*	0.189	0.00272	-1.576
	(0.00827)	(1.391)	(0.00363)	(2.052)	(0.00214)	(2.534)
commute	8.52e-05	0.0166	-1.86e-05	-0.0970***	8.07e-05***	-0.131***
	(0.000105)	(0.0176)	(4.60e-05)	(0.0260)	(2.71e-05)	(0.0321)
ethnonwhite	0.000148***	0.0350***	2.79e-05***	0.0236***	4.23e-05***	0.0506***
	(2.33e-05)	(0.00392)	(1.02e-05)	(0.00578)	(6.03e-06)	(0.00713)
income_mean	-4.22e-08**	3.08e-06	2.16e-08**	3.76e-05***	-3.44e-08***	3.21e-05***
	(2.09e-08)	(3.51e-06)	(9.18e-09)	(5.19e-06)	(5.41e-09)	(6.40e-06)
male1624	-8.13e-05	0.0115	-2.54e-06	0.0326	-4.01e-05*	0.0315
	(8.01e-05)	(0.0135)	(3.52e-05)	(0.0199)	(2.07e-05)	(0.0245)
Manufacturin	-0.00737	-6.722***	-0.00422	-2.432	-0.00202	-5.994**
g	(0.00895)	(1.505)	(0.00393)	(2.222)	(0.00232)	(2.743)
noHS	1.15e-05	0.00170	-3.76e-05**	-0.0103	1.52e-05*	-0.00399
	(3.43e-05)	(0.00577)	(1.51e-05)	(0.00851)	(8.88e-06)	(0.0105)
police	-7.24e-06	0.00699***	-8.10e-07	-0.00138	-2.81e-06**	0.00441***
	(4.58e-06)	(0.000769)	(2.01e-06)	(0.00114)	(1.18e-06)	(0.00140)
pop_density	0.00644	9.130***	0.00681	8.337*	-0.000247	9.702
	(0.0204)	(3.422)	(0.00894)	(5.051)	(0.00527)	(6.236)
retail	-0.00187	-4.805***	-0.00381	-2.676	0.000652	-5.703*
	(0.0103)	(1.730)	(0.00452)	(2.553)	(0.00266)	(3.152)
stayers	4.07e-05	0.0244***	8.79e-06	0.0266**	2.04e-05	0.0356**
	(4.89e-05)	(0.00822)	(2.15e-05)	(0.0121)	(1.27e-05)	(0.0150)
Constant	0.00943	7.605***	-0.00647	-5.777**	0.00537*	0.516
	(0.0117)	(1.962)	(0.00513)	(2.897)	(0.00302)	(3.576)
Observations	562	562	562	562	562	562
R-squared	0.549	0.539	0.503	0.446	0.586	0.431

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

bias in the regression estimates. Both simultaneity bias, in that wealthier neighborhoods have more political sway to resist the construction of stations, and omitted variable bias pose potential threats to our internal validity.

Table 3 Crime Rates are Shown to be Nearly Twice as high in Tracts with an L Stop

Variable	Obs	Mean	Std. Dev.	Min	Max
crime_withL	**124**	**.0309272**	**.0227694**	**.0050474**	**.1322268**
crime_woL	**397**	**.0169086**	**.0126368**	**0**	**.0690763**

We contend, however, that the strong significance of our estimates, especially with regard to our mobility dependent interaction terms, implies that a relationship does exist. The difficulty is then in interpreting the interaction terms. It is clear the effect of access to transit on crime is non linear with respect to mobility dependent variables like *jobaccess* and *distpoor.*

Our simple interaction term between *distpoor* and *access* demonstrates that access to transit has a dramatically negative effect on crime in areas where poor people are in close proximity, suggesting that transit enables movement to more appropriate targets. This effect may be more dramatic in Chicago than in other cities due to Chicago's well-documented income segregation. This portrait can be interpreted from the hot spot analyses maps, which depict a significant disparity between general crime rates on the impoverished South Side and property crime, which is much more significant in the wealthier North Shore, implying the use of transit to crime targets. That the interaction term using a squared *distpoor* variable is significantly positive, implies that at greater distances from poverty, the relationship becomes a predictor of crime. These estimates fit well with the theory, which predicts access to transit as enabling movement from poor neighborhoods to wealthier neighborhoods with greater payoffs.

The *jobaccess* interaction terms may be more difficult to interpret. Beginning with the squared interaction term, we would expect these results, in that increased access at greater distances (but before going out of range entirely) from jobs, increased mobility would decrease crime. The simple interaction term, however, may not derive its positive value directly from the theory; rather, it is likely this value is positive because areas with close proximity to target group appropriate jobs (primarily retail) also make good property crime targets.

Conclusions

Like most empirical studies on this theorized link, the answers remain ambiguous. This study implies that, broadly speaking, crime increases with increases in rail transit access. With the exception of the aforementioned potential for bias, we see no possible violations of least squares assumptions. On the question of external validity, however, these results should be considered carefully. Chicago is unique for its income and ethnic segregation, which would be expected to make these effects more dramatic. Moreover, 2013 was a unique year for Chicago crime trends, as the city saw an overall drop in rates to levels unseen since the 1960's. As such, these results should not be considered final, or conclusive in any real way.

Moreover, these results imply, as Ihlanfeldt and others have noted, that the effect of access to transit on crime rates is dependent upon neighborhood characteristics. A rail stop in a suburban neighborhood may enable criminal entry, while a rail stop in the inner city may enable just the opposite. These results cannot simply be used to say whether or not transit increases crime; rather, they should be used to carefully consider more complex relationships.

Ultimately, these estimates are rudimentary, and possess a significant potential for improvements. Nonetheless, we hope that they will encourage deeper probing into these relationships, so that our understanding of the forces that shape our neighborhoods may continue to improve.

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