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Rail Transit and Neighborhood Crime: The Case of Atlanta, Georgia

Keith R. Ihlanfeldt*

The construction of commuter rail stations is the centerpiece of many metropolitan areas' overall strategies for dealing with worsening air pollution, automobile congestion, and urban sprawl. Neighborhood groups have frequently opposed new stations on the grounds that stations increase crime. If fears of station-induced neighborhood crime are justified, building new stations may make the problems they are supposed to address even worse, because crime is a cause of employment and population decentralization. This paper first demonstrates theoretically that transit's impact on neighborhood crime can be either positive or negative. Some rare evidence is then provided on the link between transit and crime. Using a unique panel of neighborhood crime data for Atlanta, the results from estimating fixed effects and random effects models show that transit's impact on crime depends on certain characteristics of the neighborhood. The mix of these characteristics found within central city neighborhoods has resulted in transit increasing crime there, whereas in the suburbs crime has been reduced by transit.

1. Introduction

In a growing number of metropolitan areas, the construction or extension of a rail transit system has been advocated by policy makers as a way to address the numerous externalities associated with a heavy reliance on the automobile for the journey to work. However, in many of these same areas, rail transit proposals have encountered significant opposition from neighborhood groups (Pendered 1997; Carlson 2000; Stingl 1996; Byrd 1989; Gayle 1989; Armacost 1994; Kane and Lee 1994; Tandon 1999). These groups fear that a rail station placed in or near their neighborhood will increase neighborhood crime, because this would provide criminals improved access to the neighborhood.[1] If these fears are justified and transit stations do increase neighborhood crime, this may counteract one of the principal objectives of the new transit proposals: to reduce urban sprawl by attracting population and employment to station areas. Crime has been found to strongly affect the intrametropolitan location decisions of firms and households (Mills 1992; Cullen and Levitt 1999; Bollinger and Ihlanfeldt 2000). Hence if station-induced crime is a reality, station openings may worsen, rather than mitigate, urban sprawl. In addition, to achieve transit-oriented development, significant subsidies may be required to offset the cost of crime.

There are reasons to believe, however, that the opening of a rail station may actually cause neighborhood crime to fall, rather than rise. Although the station may increase access to the

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* DeVoe Moore Center and Department of Economics, 150 Bellamy Building, Florida State University, Tallahassee, FL 32306-2220; E-mail kihlanfe@mailer.fsu.edu.

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[1] Typical of these fears are those expressed by residents of this paper's study area (Atlanta, Georgia). For example, Atlanta resident Steve Spellman was quoted in Pendered (1997) as having said, "Having MARTA [rail] increases the chances of crime. The criminals can get off the train and break into your home and get back onto the train. I don't think that's as likely to happen on buses, where they have to walk past the driver to get on board."

neighborhood by outside criminals, it may also induce criminals living within the neighborhood to commit their crimes elsewhere by lowering commuting costs between the home neighborhood and other neighborhoods. Moreover, the station may increase the job accessibility of neighborhood residents, especially that of crime-prone youth, thereby increasing the opportunity cost of crime. Hence the net effect of rail transit on neighborhood crime can be either positive or negative, depending on the relative magnitudes of the above three factors.

This paper provides some rare evidence on the relationship between rail transit and neighborhood crime. First, the economic model of crime is extended by adding a spatial dimension: criminals are mobile across neighborhoods and commit their crimes where net returns are the highest. Based upon this spatial model of crime, estimable models of neighborhood crime are developed, which include the percentages of the neighborhood served by rail transit as an explanatory variable. To estimate these models, a unique panel database for the Atlanta region that includes four consecutive years of crime data for each of 206 census tracts is used. With these data, neighborhood crime models are estimated for total crime and separately by crime category (property crime versus violent crime) using both fixed effects (FE) and random effects (RE) models.

The results show that rail stations have a statistically significant effect on neighborhood crime and that the effect varies with three characteristics of the neighborhood: median income level, density of poverty, and average distance to poor people living outside the neighborhood. The mix of characteristics found within central city neighborhoods has resulted in transit increasing crime there, whereas in the suburbs transit has reduced crime in white neighborhoods and has had no effect on crime in black neighborhoods. The results suggest that the fears expressed by suburban residents over station-induced neighborhood crime are unfounded and that extensions of rail transit into the suburbs will not cause further decentralization of population and employment. However, to maximize transit-oriented development around central city stations, greater police surveillance within transit neighborhoods may be necessary.

2. Literature Review

Only four studies provide evidence on whether rail stations increase neighborhood crime, with findings evenly split against and in favor of the hypothesis that transit causes crime. In a study of the Baltimore Metro system, Plano (1993) looked at trends in crime rates for neighborhoods surrounding three rail stations using data from years just before and just after the stations opened, comparing these to trends in crime rates for Baltimore County as a whole. No significant relationship was found between the trends in crime rates and the opening of the rail stations. However, there were no controls for other factors that might have affected crime rates.

In a study of the Metropolitan Atlanta Rapid Transit Authority (MARTA) system, Poister (1996) also looked at time series data of criminal activity near rail stations before and after station opening dates. The study considered only two contiguous stations on the same section of the rail line, using neighborhood and county monthly crime data over a four year period. The poststation period was limited to just 18 months. The graphical "event study" depiction of neighborhood crime rates before and after the station openings showed little or no overall impact on crime rate trends in the neighborhoods surrounding the stations. A simple regression model attempting to measure changes in the overall trend in crime rates near the stations both before and after the station opening dates also offered little evidence to support the hypothesis that rail stations cause an increase in local crime. However, like Plano (1993), Poister (1996) used only the opening dates of the stations to explain changes in crime rate trends, ignoring other explanatory factors that may have been correlated with these dates.

Bowes and Ihlanfeldt (2001) also used Atlanta data to estimate a simple neighborhood crime model that served as an auxiliary equation to their hedonic price analysis of the impact of MARTA rail stations on residential property values. The crime model was used to estimate the indirect effects that stations may have on the values of nearby properties by attracting criminal activity to station areas. In their basic model, Bowes and Ihlanfeldt (2001) found that the density of neighborhood crime is higher in those census tracts whose centroids are within a quarter mile of a station. However, in a model containing interactions, the latter effect was found to vary with neighborhood income, distance from downtown, and whether the station had a parking lot.[2]

Finally, Block and Block (2000) mapped reported street robberies (actual and attempted) on Chicago's Northeast Side and within the Bronx borough of New York City. For both of these places they found that there was a strong relationship between street robbery and propinquity to a rapid transit station. The number of robberies tended to peak a few blocks away from the stations.

3. A Spatial Economic Model of Crime

The economic model of crime (Becker 1968) is aspatial in the sense that all crimes are assumed to be committed by residents of the home community. This assumption is untenable if the objective is to explain neighborhood crime when criminals are mobile across neighborhoods. In this section a simple model that adds a spatial dimension to the standard crime model is presented. The objectives are twofold. The first objective is to identify those factors that account for differences in the amount of property crime across neighborhoods. The model is also relevant to that subset of violent crimes that are economically motivated. The second objective is to relate these factors to the percentage of the neighborhood that is served by rail transit.

Consider the average resident (R) of neighborhood H. Assume that within a given time period, he must decide whether he will commit a crime and whether this crime will be committed within the home neighborhood. The joint probability that he is a criminal and commits his crime in H equals the marginal probability that he is a criminal times the conditional probability that he commits the crime in the home neighborhood given that he is a criminal:

$$P_{\mathrm{H}}^{\mathrm{R}} = P^{\mathrm{R}}(C) \times P^{\mathrm{R}}(\mathrm{H} \mid C). \tag{1}$$

The factors that determine the marginal probability are identified by the standard crime model. In this model, the expected net return (π) from committing a crime is defined as the expected payoff (w) minus the direct cost incurred in committing the crime (c) minus the product of the probability of apprehension and conviction (p) and the prospective penalty if convicted (f):

$$\pi = w - c - pf. \tag{2}$$

The expected net return from committing a crime can be defined separately for a crime committed by the resident within his home neighborhood (π_{H}) and outside his home neighborhood (π_{O}):

[2] Although this paper relies on some of the same data as Bowes and Ihlanfeldt (2001), there is little similarity between their models and the models estimated here. The latter are based on a stronger theoretical underpinning and include a more refined set of both crime measures and explanatory variables. In addition, Bowes and Ihlanfeldt (2001) do not investigate differences in rail transit's effect on crime between central city and suburban neighborhoods, which is a major focus of the current paper.

$$\pi_H = w_H - p_H f, \tag{3}$$

$$\pi_O = w_o - p_o f - t_o, \tag{4}$$

where c is limited to the costs of commuting to the crime (t_o), which are assumed to be negligible if the crime is committed within the home neighborhood. The resident will be a criminal if the maximum expected net return from crime exceeds the benefit of being law-abiding, which equals foregone expected earnings in legitimate activity (e) net of journey-to-work costs (j) plus the monetary equivalent of the psychic return from good citizenship (g):

$$\max(\pi_H, \pi_o) > e - j + g. \tag{5}$$

Given that Equation 5 is satisfied, the resident who is a criminal will commit his crime in H only if the expected net return from crime is higher there than elsewhere:

$$\pi_H > \pi_o. \tag{6}$$

Equation 5 defines the variables that affect the marginal probability, whereas Equation 6 defines the variables that affect the conditional probability. Together these are the variables that affect the joint probability:[3]

$$P_H^R = f(w_H, w_O, p_H, p_o, t_o, e, j, g). \tag{7}$$

Although the above model adds a spatial dimension to the economic model of crime, Equation 7 provides limited guidance on how this dimension might be incorporated into an empirical model, since it is unclear how to operationalize the concept "outside the home neighborhood." To further refine the spatial dimension of the model, it is assumed that t_o is proportional to travel time. Travel time is equal to distance times the inverse of the speed of travel. Two implications can be drawn from this assumption. First, expected net returns to crime outside the home neighborhood rise as crime targets with higher payoffs or lower probabilities of apprehension are found closer to the home neighborhood. Second, net returns will also rise if travel times decline, holding distances constant.[4] These implications suggest that Equation 7 be rewritten as

$$P_H^R = f(w_H, p_H, e, j, g, A_H, S_H), \tag{8}$$

where A_H is the proximity to high payoff crimes (net of expected penalties) outside the home neighborhood, and S_H is the speed of travel from H to other neighborhoods.[5] The total amount of crime in H committed by residents equals P_H^R times the number of residents.

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[3] Because the study area includes only neighborhoods located within the same state, f can be treated as a spatial constant and therefore excluded from Equation 7. However, the two counties included in the area do have their own judicial circuit courts, and sentences may vary between these courts. To the extent that perceived differences in f between the two counties that arise because of differences in sentencing are time invariant, they are controlled for the estimated models. If intercounty perceptions of f change over the four years covered by the panel, this will bias the estimated effects of rail transit on crime density only if these changes are correlated with the census tract measure of transit access. There are no obvious reasons to expect this correlation.

[4] Higher travel times may reduce net expected payoffs for reasons other than the direct costs associated with travel. For example, Glaeser and Sacerdote (1996) note that the probability of arrest may vary directly with travel time: the longer it takes to return to a safe haven after committing a crime, the higher the probability of apprehension. Other reasons the probability of arrest may vary directly with travel time are (i) criminals may have less knowledge of distant areas, making it more difficult to escape; and (ii) criminals may be more recognizable as nonresidents in neighborhoods more distant from home.

[5] The model assumes that there is substitution between crime committed at home and crime committed other places so that rail access will reduce local crime. There is the possibility that a home criminal could continue to commit as many crimes within the home neighborhood as before rail access, and after his neighborhood obtains rail access also commit crimes in other neighborhoods. The assumption that there is spatial substitution by the home criminal is reasonable as long as time is considered a binding constraint.

Crimes in H are also committed by outsiders. The joint probability that the average outsider is a criminal and commits his crime in H is

$$P_{\rm H}^{\rm O} = P^{\rm O}(C) \times P^{\rm O}({\rm H} \mid C). \tag{9}$$

As is true for a resident, an outsider will be a criminal only if the expected net return from crime exceeds the benefit of being law abiding. However, the factors that determine the marginal probability [$P^{\rm O}(C)$] that the average outsider is a criminal are constant across neighborhoods. Hence only the factors that determine the conditional probability [$P^{\rm O}({\rm H} \mid C)$] are relevant.[6] Given that the average outsider is a criminal, the crime will occur in H only if the expected payoff net of expected penalties and commuting costs is higher there than elsewhere:

$$w_{\rm H} - p_{\rm H} f - t_{\rm H} > w_{\rm O} - p_{\rm O} f - t_{\rm O}. \tag{10}$$

This condition implies that $P^{\rm O}({\rm H} \mid C)$ will vary inversely with $P_{\rm H}$ and directly with $w_{\rm H}$. $P^{\rm O}({\rm H} \mid C)$ will also vary directly with the proximity of H to the average outside criminal (N) and the speed of travel to H from other neighborhoods, because each of these factors increase net returns from crime in H by decreasing $t_{\rm H}$.[7,8] Thus,

$$P^{\rm O}({\rm H} \mid C) = f(p_{\rm H}, w_{\rm H}, {\rm N}_{\rm H}, S_{\rm H}). \tag{11}$$

The total amount of crime in H committed by outside criminals equals $P^{\rm O}({\rm H} \mid C)$ times the number of outside criminals.

The total amount of crime in H ($C_{\rm H}^{\rm T}$) is the sum of the crimes committed by residents ($C_{\rm H}^{\rm R}$) and by outsiders ($C_{\rm H}^{\rm O}$):

$$C_{\rm H}^{\rm T} = C_{\rm H}^{\rm R} + C_{\rm H}^{\rm O}. \tag{12}$$

Hence collecting together the arguments in Equations 9 and 12 yields:[9]

$$C_{\rm H}^{\rm T} = f(j, e, g, w_{\rm H}, p_{\rm H}, A_{\rm H}, S_{\rm H}, N_{\rm H}). \tag{13}$$

Turning to the effect of transit on neighborhood crime, the percentage of the neighborhood served by rail transit (T) may affect $C_{\rm H}^{\rm T}$ by reducing the average journey-to-work costs of neighborhood residents (j) and by increasing the average speed of travel between locations within H and other neighborhoods ($S_{\rm H}$). Suppressing H subscripts, the partial derivative of neighborhood crime with respect to transit can be expressed as

$$\partial C^{\rm T}/\partial {\rm T} = \partial C^{\rm R}/\partial S \times \partial S/\partial {\rm T} + \partial C^{\rm O}/\partial S \times \partial S/\partial {\rm T} + \partial C^{\rm R}/\partial j \times \partial j/\partial S \times \partial S/\partial {\rm T}. \tag{14}$$

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[6] Another way to see this is that there is little difference in the stock of outside criminals from the perspective of any two neighborhoods, assuming the community is composed of many small neighborhoods.

[7] Each of the variables in Equation 11 is more precisely defined as the value of the variable in neighborhood H relative to other neighborhoods. However, because H is one of many neighborhoods, the expected value outside of H can be treated as a constant.

[8] The assumption that the average speed of travel from H to O is the same as from O to H implicitly assumes that the transportation mode split is the same among residents leaving the neighborhood as for outsiders coming into the neighborhood. The latter assumption is not necessary but is useful in simplifying the equations.

[9] The number of neighborhood residents and the number of outside criminals do not appear in Equation 13 if neighborhoods all have the same population and the number of outside criminals is roughly the same across neighborhoods. The latter is expected if the community contains many neighborhoods. These conditions are approximated for the sample of neighborhoods used in the empirical estimation.

In the first term on the right-hand side of Equation 14, $\partial S/\partial T$ registers the effect on the average speed of travel from locations inside the neighborhood to destinations outside the neighborhood from an increase in the percentage of the neighborhood served by transit. Transit increases the average speed of travel to other neighborhoods and thereby reduces the probability that the average resident will commit his crime in the home neighborhood. The first term is therefore negative in sign. The second term on the right-hand side of Equation 14 is the effect that transit has on crime from opening up the neighborhood to outside criminals. As the percentage of the neighborhood served by transit increases, the average speed of travel from outside the neighborhood to locations within the neighborhood declines, which causes more crime by outsiders.[10] The second term is therefore positive in sign. The final term on the right-hand side of Equation 14 shows the effect of transit on the journey-to-work costs of neighborhood residents. As more of the neighborhood is served by transit, a greater percentage of the neighborhood's residents experience a decrease in journey-to-work costs and thereby enhanced accessibility to jobs. This term has a negative sign. Because the first and third terms of Equation 14 are negative and the middle term is positive, the sign on $\partial C^{T}/\partial T$ is ambiguous and must be determined by empirical investigation.

The theoretical model suggests that the partial derivative of neighborhood crime with respect to transit will vary across neighborhoods, because in Equation 14 the magnitudes of $\partial C^{R}/\partial S$, $\partial C^{O}/\partial S$, and $\partial S/\partial T$ all vary. In the case of $\partial C^{R}/\partial S$, if the expected payoff from crime within the home neighborhood (w_{H}) is sufficiently high, the expected net return from crime will remain higher there than elsewhere even if travel times decline to other neighborhoods. Similarly, if expected payoffs outside the home neighborhood (A_{H}) are sufficiently low, a reduction in travel times will not entice residents to commit their crimes outside the home neighborhood. On the other hand, for a sufficiently low value of w_{H} or a sufficiently high value of A_{H}, the expected net return from crime will be higher outside the home neighborhood both before and after a unit increase in S_{H}. Hence the absolute magnitude of $\partial C^{R}/\partial S$ will be relatively small at low and at high values of w_{H} and A_{H}, implying dome-sloped relationships between $|\partial C^{R}/\partial S|$ and each of these variables.

In the case of $\partial C^{O}/\partial S$, if the expected payoff from crime in H (w_{H}) is sufficiently high, the outside criminal will find that the expected net return from crime is higher in H than elsewhere both before and after a unit increase in S_{H}. Similarly, if the outside criminal lives sufficiently close to H, implying a high value of N_{H}, the expected net return to crime will be higher in H both before and after an increase in S_{H}. On the other hand, for a sufficiently low value of w_{H} or N_{H} (the latter indicating the criminal lives a long distance from H), the expected net return from crime will be relatively low in H even after a reduction in travel time to H. Again, dome-sloped relationships are implied between $|\partial C^{O}/\partial S|$ and w_{H} and N_{H}.

Finally, the absolute magnitude of $\partial S/\partial T$ is expected to be larger in poor neighborhoods. The residents in poor neighborhoods are more dependent on public transit, so the availability of rail transit causes a larger switch from buses. Because the time savings are larger going from bus to rail than from auto to rail, the average resident of a poor neighborhood experiences a relatively greater reduction in S from an increase in T.

[10] It may be difficult to see how reducing the average speed of travel between the home neighborhood and other neighborhoods can cause both an increase in crime by outsiders and a reduction in crime by insiders. This can be seen by a simple example. Assume that along a radial subway line there are three stations A, B, and C that are located at successively greater distances from downtown. In the neighborhoods served by A, B, and C, expected payoffs to crime are poor, good, and excellent, respectively. The existence of the rail line will cause criminals living in A's neighborhood to commit their crimes in B's neighborhood and will cause criminals living in B's neighborhood to commit their crimes in C's neighborhood.

4. Data and Empirical Model

Reported crimes at the census tract level are available for the City of Atlanta and DeKalb County for the years 1991–1994. The City of Atlanta, which is mostly in Fulton County, shares a long common boundary with DeKalb County on the city's east side. Together, Atlanta and DeKalb represent the central most portion of the Atlanta region. In 1994, roughly 1 million people lived in the 206 census tracts found within the Atlanta/DeKalb area. Within this area there were 31 MARTA rail stations in 1994.

Crimes include those tracked by the U.S. Federal Bureau of Investigation (FBI) and labeled by the FBI as "Part I crimes." These crimes are broken down into property crime (burglary, car theft, and larceny) and violent crime (homicide, rape, assault, and robbery). Reported crimes committed on MARTA station property for the same years represented in the crime panel were obtained from MARTA. With the latter data, total, property, and violent neighborhood crimes net of crimes committed on station properties were computed.

In addition to the Atlanta/DeKalb area, a larger seven-county area is used in the construction of some of the independent variables in order to avoid boundary effects and to represent the local labor market.[11] This area includes the two central counties of Fulton and DeKalb as well as the five surrounding counties of Cobb, Douglas, Gwinnett, Clayton, and Rockdale. In addition to the crime data, data from other sources are used in the construction of the independent variables, as noted in Table 1. Means and standard deviations for all variables can be found in the Appendix for the full sample of tracts and separately for tracts containing and not containing a MARTA station impact area.[12]

With these data, versions of the following model are estimated:

$$C_{it} = \alpha + X_{it-1}\beta + W_{i1990}\gamma + v_i + e_{it}. \tag{15}$$

The primary dependent variable is the density of crime (i.e., crimes per acre) within-tract i in year t for one of the crime measures. Although the crime rate (number of crimes/population) is the more commonly used crime measure, crime density is the more appropriate variable if the objective is to explain the spatial distribution of crimes across neighborhoods.[13,14] However, for the sake of comparison, both the crime density and the crime rate alternatively serve as the dependent variable in the estimation of the FE models. Also, as noted below, the major conclusions of this study hold regardless of whether the number of crimes is adjusted by the area or the population of the tract. Because the interest is in the effect of rail access on crime in the area surrounding the rail station, the number of crimes committed on station property is subtracted from the total number of tract crimes in

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[11] By boundary effects I am referring to the problem of measuring variables that describe conditions outside the tract. For these variables (specifically, the tract's proximity to jobs or to poor people, as described below), a larger geographical area that is centered on the study area is required. The seven-county Atlanta region satisfies this requirement.

[12] A MARTA station impact area is a circle centered on the station with a quarter mile radius. This is defined more completely below.

[13] The primary problem with the crime rate is that many neighborhoods contain nonresidential crime targets (e.g., commercial and industrial property), which will affect crime density, but not the crime rate, in a consistent fashion across tracts. These nonresidential targets are included among the set of explanatory variables (see Table 1) and are found to be highly significant. It is also worth noting that the primary argument for using the crime rate—that it measures the individual resident's risk of victimization—is less defensible at the neighborhood level. As Harries (1981) notes, the reliability of the crime rate as an indicator of residents' probability of being victimized declines as the level of business activity within the neighborhood expands.

[14] The focus on crime density is also motivated by previous research, which finds that the density of crime within the neighborhood has an effect on residential property values that is three times larger than the effect produced by the neighborhood crime rate (Bowes and Ihlanfeldt 2001). In this 2001 paper, crime density has the stronger effect because it has a greater influence on residents' perceptions of whether a crime problem exists within their neighborhood.

Table 1. Variable Descriptions

Variable	Description	Source	Link to Theory
Time varying (X)			
marta	Percent of tract within quarter mile of rail station	Map	j, S
jaccess	Job accessibility of young men	ARC, PUMS[a]	j
medinc	Tract median income/$10,000	Donnelly[b]	w, p
year 92–year 94	Year dummy variables		
Time invariant (W)			
distpoor	Average distance to poor people	Census[c]	A, N
povden	Tract poverty density	Census	e, g
under1519	Tract density of men age 15–19	Census	e, g
under2024	Tract density of men age 20–24	Census	e, g
hsgrads	Tract density of persons over 18 with high school diploma	Census	e, g
stayers	Tract density of persons who have lived in tract 5 or more years	Census	p
vacant	Density of vacant housing	Census	p
population	Tract population density	Census	w, p
blacks	Tract black density	Census	e, g
retail	Tract retail employment density	ARC	w
mfg	Tract manufacturing employment density	ARC	w, p
police	Density of police officers in jurisdiction containing tract	FBI[d]	p
highway	Tract with controlled access highway	Map	S

[a] ARC, Atlanta Regional Commission; PUMS, Public Use Micro-data Sample.
[b] Donnelly Marketing, Inc. Donnelly's median income estimates are updates of decennial census numbers obtained via multivariate modeling techniques that utilize data from telephone surveys and secondary resources.
[c] 1990 Census of Population and Housing, Summary Tape File 3A.
[d] U.S. Department of Justice, Federal Bureau of Investigation Uniform Crime Reports. Census tracts are assigned to a police jurisdiction using the MABLE/Geocorr Software from the U.S. Census Bureau.

forming our dependent variables.[15] However, none of the conclusions of this study depend on making this adjustment.

The values of the X variables vary over both space and time and are lagged one year. Lagging is done for two reasons. First, agents acting at the beginning of the year do not have perfect foresight of conditions later in the year. The discrete time intervals defining the data therefore dictate the use of a one-year lag. Second, lagging reduces the potential for endogeneity of the independent variables to bias the results. However, this concern is minimal in the case of rail access. The MARTA rail line as presently configured was initially planned over 25 years ago. The phased implementation of the plan, resulting in stations opening over the years 1979 to 2001, was necessitated by budgetary constraints.[16]

[15] The reader may be interested in the amount of crime that occurs at the rail stations. For the final year of the panel (1994), the amount of reported crime committed on station property averaged across the 31 MARTA stations equaled 33 property crimes and six violent crimes. For each census tract containing a rail station, reported station crimes were computed as a percentage of all reported crimes committed within the tract. On average, this percentage is 8% for property crime and 7% for violent crime.

[16] To investigate whether our results might be biased by endogeneity despite the use of one-year lags, we also ran regressions lagging all of the regressors two years. As expected, this increased the standard errors of our estimated parameters, but there was little effect on the estimated partial derivatives reported in Tables 4 and 5.

The W variables come primarily from the 1990 Census of Population and Housing and, as such, have values that vary over tracts but not over time.[17]

Note that Equation 15 includes two error terms: v_i is tract-specific; it differs between tracts but, for any particular tract, its value is constant. It is included to account for crime-related unobserved heterogeneity across tracts. e_{it} is the "usual" residual with the usual properties. This error structure necessitates the use of either a FE or RE model. The essential difference between these two estimators is that RE is based upon variation in the data across and within tracts, whereas FE ignores variation across tracts and relies solely on within-tract variation to obtain its estimates. For short and wide panels like the one used here, it is frequently the case that there is insufficient variation over time to obtain precise parameter estimates with FE. In the present case, four MARTA rail stations opened over the years covered by the crime panel, resulting in 9–20 tracts experiencing a change in rail transit access, depending on the size of the rail station impact area (defined below). Hence there is variation in the key test variable. However, the theory presented in section 3 indicates that the effect of rail access on neighborhood crime depends on certain neighborhood characteristics. To capture these dependencies, it is necessary that the rail access variable be interacted with five different neighborhood descriptors, as described in detail below. As discussed in section 6, all of these interaction terms are statistically significant. The within-tract variation of rail accessibility that is available within the crime panel is too limited to reliably estimate the coefficients on rail access and all of its interactions with these other variables, which precludes the use of FE. In fact, given the complexity of MARTA's effect on neighborhood crime, even a much longer panel than the one we use would probably not resolve this problem. Fortunately, however, by drawing upon the full variation in the data (both within and between tracts), it is possible to estimate the MARTA parameters with some confidence using RE. Because there is sufficient within-tract variation to estimate FE models that include a more limited set of interaction variables, results from these models are also reported below.

The principal concern that arises when using RE is that the consistency of its estimates hinges upon the orthogonality between v_i and the regressors. Of course, it is also assumed, as in ordinary least squares (OLS), that the regressors are uncorrelated with e_{it}. Correlations between the regressors and the error terms result from the omission of important explanatory variables from the model. Because our models explain roughly 90% of the neighborhood's density of crime, we believe that it is unlikely that an important variable has been omitted from our models. Additional support for the assumption that v_i is orthogonal to the regressors comes from conducting a Hausman (1978) test. As noted below, the test results indicate that for all of our estimated crime models, the null hypothesis that v_i and the regressors are uncorrelated cannot be rejected at conventional levels of statistical significance.[18]

The key explanatory variables entering Equation 15 are the neighborhood's access to a rail station and the neighborhood variables that are interacted with the rail access variable. Rail access is alternatively defined as the percentage of the tract within a quarter mile, half mile, or three quarters of a mile of a rail station. The results reported below use a circle with a quarter-mile radius as the rail station impact area, because this variable (marta) provided the greatest explanatory power. The results, however, are robust to the size of the impact area. The theory presented in section 3 indicates that the

[17] All of the W variables identified in Table 1 are measured for 1990. Most of these variables are from the 1990 Census. However, a number of the variables from other sources (police, retail, manufacturing) are available on an annual basis and could have been treated as X variables. Yet there is almost no variation in these variables within tracts over the short time period covered by the crime panel: In all cases the coefficient of variation of the deviation from the tract mean is less than one.

[18] The Hausman test only tests whether the X variables are uncorrelated with v_i. The W variables are not tested. However, all of the key variables (i.e., rail access and the interactions between rail access and the neighborhood descriptors) fall into the X group of variables.

effect of rail transit accessibility on neighborhood crime varies nonlinearly with w, N, and A. w is the expected payoff to crime inside the neighborhood. Although a number of the explanatory variables proxy w, the measure of greatest interest and arguably the single proxy most highly correlated with the criminal's true expected bounty is the neighborhood's median income. Both residential and commercial loot tend to be high in neighborhoods with higher income households. To capture transit's nonlinear effect with w, marta is therefore interacted with the median income of the neighborhood and the square of median income. A is the proximity of the neighborhood to crime targets outside the neighborhood with high expected payoffs (net of their expected penalty), whereas N is the neighborhood's proximity to outside criminals. Both A and N are proxied by the distance of the tract to poor people. This is based on the expectation that if poor people surround the tract, A will tend to be low, whereas N will tend to be high.[19,20] The distance to the poor is measured for tract i as

$$\text{distpoor}_i = \sum_{j=1}^{J} \text{poor}_j \times d_{ij}, \tag{16}$$

where poor_j is the fraction of the seven-county region's poverty population living in tract j, and d_{ij} is the distance in miles between the centers of tracts i and j. To capture transit's nonlinear effect with N and A, marta is interacted with distpoor and distpoor squared.[21] Finally, the theory suggests that rail access will increase the opportunity cost of crime more within those neighborhoods with higher densities of poor people. To capture this effect, marta is interacted with the density of poverty within the neighborhood.

Among the remainder of the explanatory variables defined in Table 1, only the construction of the neighborhood's access to jobs (jaccess) is sufficiently complicated to require further comment. This variable is based on Raphael (1998), who shows that employment-growth–based measures of job access are superior to alternative measures. Because crimes are disproportionately committed by young men, jaccess measures the growth in jobs suitable for 16- to 24-year-old men:

$$\text{jaccess}_{it} = \sum_{j=1}^{J} \sum_{k=1}^{K} a_{jk} \times G_{jkt} \times \exp(-\gamma d_{ij}), \tag{17}$$

where G_{jkt} is the change in employment within industry k in tract j during year t; a_{jk} is the estimated fraction of jobs within industry k and tract j suitable for men aged 16 to 24; d_{ij} is the distance in miles between the centroids of neighborhoods i and j; and γ is the "distance-decay" function. The latter serves to place more weight on job openings located closer to home.[22] Estimates of G_{jkt} are based on the annual census tract employment estimates provided by the Atlanta Regional Commission (ARC).[23] The a_{jk} come from a matrix formed from the 1990 Public Use Micro-data Sample (PUMS)

[19] Expected payoffs are higher in neighborhoods containing nonpoor people. Expected penalties are also higher in these neighborhoods because greater investments in private protection increase the probability of apprehension. Therefore, A will increase with the average distance to poor people only if expected payoffs rise more rapidly than expected penalties.

[20] A strong correlation between crime and poverty is a consistent finding in the literature. For some recent evidence, see Center for Urban Poverty and Social Change, Case Western Reserve University, http://povertycenter.cwru.edu.

[21] Because $\partial C^{O}/\partial S$ and $\partial C^{R}/\partial S$ have opposite signs in the theoretical model, the expected signs on marta $\times$ distpoor and marta $\times$ distpoor^2 are ambiguous and the estimated signs will depend on the relative strengths of the two effects.

[22] To obtain an estimate of γ, a trip-distribution gravity model is commonly estimated to isolate the effect of distance on intrametropolitan youth labor mobility. Because commuting data at the tract level are not available for Atlanta youth, Raphael's (1998) automobile travel time–based estimate of γ for San Francisco youth was converted into a miles-based estimate for Atlanta youth.

[23] ARC's census tract employment estimates, which are provided separately for each of eight major industry groups, are based on firm-level ES-202 unemployment insurance data from the Georgia Department of Labor. ARC researches each firm and assigns its jobs to individual tracts. Noncovered employment is accounted for by directly surveying noncovered establishments.

Table 2. Fixed Effects Models

	Total Crime Density	Total Crime Rate	Property Crime Density	Property Crime Rate	Violent Crime Density	Violent Crime Rate
marta	0.0717	0.0119	0.0100	0.0125	0.0117	0.0006
	(1.09)[a]	(2.49)	(1.08)	(2.92)	(0.87)	(0.74)
marta × medinc	0.0350	0.0124	0.0180	0.0118	0.0170	0.0007
	(3.94)	(5.87)	(4.39)	(6.19)	(2.84)	(1.91)
marta × medinc^2	−0.0086	−0.0027	−0.0044	−0.0024	−0.0042	−0.0003
	(3.45)	(4.55)	(3.85)	(4.55)	(2.48)	(2.78)
medinc	0.0261	0.0004	−0.0123	−0.0027	0.0384	0.0031
	(0.26)	(0.02)	(0.26)	(0.12)	(0.57)	(0.75)
medinc^2	−0.0021	0.0000	0.0004	0.0002	−0.0025	−0.0002
	(0.26)	(0.00)	(0.13)	(0.13)	(0.48)	(0.06)
jaccess	−0.0006	−0.0002	−0.0005	−0.0002	−0.0002	−0.0001
	(2.52)	(3.56)	(4.05)	(3.50)	(0.96)	(2.46)
Year 1992	0.1100	0.0155	0.0550	0.0084	0.0548	0.0071
	(1.81)	(1.07)	(1.96)	(0.64)	(1.34)	(2.86)
Year 1993	0.1843	0.0444	0.1013	0.0328	0.0830	0.0115
	(2.26)	(2.27)	(2.68)	(1.48)	(1.51)	(3.45)
Year 1994	0.1559	0.507	0.1012	0.0422	0.0546	0.0085
	(1.52)	(2.06)	(2.14)	(1.92)	(0.79)	(2.02)
Constant	1.0002	0.2207	0.736	0.1808	0.2663	0.0398
	(4.03)	(3.71)	(6.41)	(3.39)	(1.59)	(3.92)
R^2	0.105	0.006	0.282	0.001	0.027	0.206

[a] Absolute value of *t*-statistic in parentheses.

for Atlanta. This matrix contains eight industry rows (the same industry groups used by ARC) and seven county columns (those forming the broader Atlanta region identified above). Within each cell the percentage of jobs held by 16- to 24-year-old men without college degrees was computed from the PUMS. The multiplication of G_{jkt} by a_{jk} therefore provides an estimate of the number of new jobs in a particular industry within a tract located in a particular county that are available to (and taken by) young men.

5. Fixed Effects Models

The means and standard deviations of all of the variables are presented in the Appendix. Separate sets of statistics are reported for the full sample of tracts, tracts with rail access (marta > 0), and tracts without rail access (marta = 0). Neighborhoods with rail access have higher crime, lower median incomes, and higher densities of blacks, poor people, and retail and manufacturing employment than neighborhoods without rail access. These results are not surprising because Atlanta's demographic and employment gradients are typical of a large metropolitan area (Muth 1969), and MARTA tracts are, on average, located closer to the metropolitan center than non-MARTA tracts.

The FE models include the rail access variable (marta) along with its interactions with the median income of the neighborhood (marta × medinc) and its square (marta × medinc^2). Also included are the rest of the time-varying variables (see Table 1). Results are reported in Table 2 for total crime, property crime, and violent crime using both the density of crime and the crime rate as dependent variables. For all six models, the three marta variables are jointly significant at the 1%

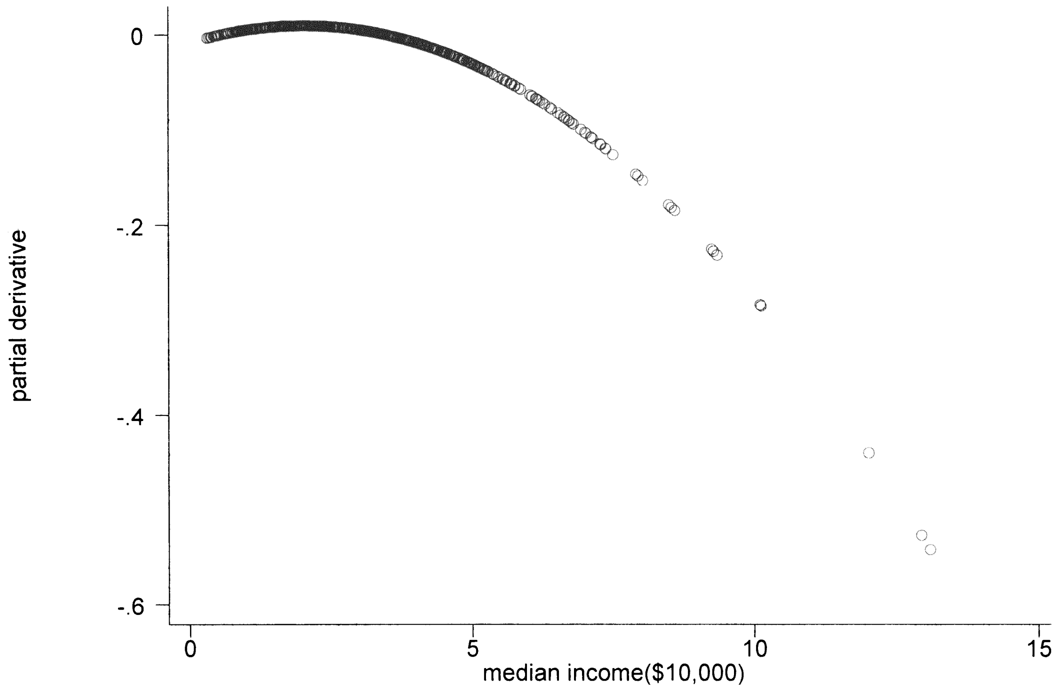

Figure 1. Partial Derivative of Property Crime Density with Respect to Rail Access as a Function of Neighborhood Income

level, which indicates that rail access has a statistically significant effect on neighborhood crime. In all cases this effect is found to vary nonlinearly with the median income of the neighborhood—the estimated coefficient on marta $\times$ medinc is positive and significant—whereas the estimated coefficient on marta $\times$ medinc^2 is negative and significant. To visualize how the crime effect of rail access depends on neighborhood income, the partial derivative of property crime density (property crime rate) with respect to rail access is graphed as a function of median income (see Figure 1 and Figure 2).[24] There is little difference between the crime density and crime rate graphs. For crime density, the partial derivative is a small negative number below 6,500, between $6,500 and $33,000 it is a positive number that peaks at $20,000, and above $33,000 it becomes increasingly negative. These results, which parallel those reported below for the RE models, suggest that rail access has opposite effects on central city versus suburban neighborhoods. In the typical central city neighborhood (median income in 1994 = $24,799), rail access has a positive effect on crime, whereas in the typical suburban neighborhood (median income in 1994 = $41,084), rail access reduces crime.[25]

The FE models also show that median income has no effect of its own on crime and that better access to jobs suitable for young men reduces crime. These results are also consistent with those reported below from the RE models.

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[24] The graphs for total and violent crime are highly similar to those for property crime.

[25] The results reported in Table 2 use a quarter mile as the rail station impact area. Using this variable, nine neighborhoods experienced a change in rail access over the panel period. These neighborhoods represented a wide range of income levels (mean median income = $25,479 with a standard deviation of $10,527). FE models were also estimated using a half mile and three quarters of a mile as the size of the impact area. Using these variables, 13 and 20 neighborhoods experienced a change in rail access, respectively. There is little difference between the results using these larger impact areas and those reported in Table 2.

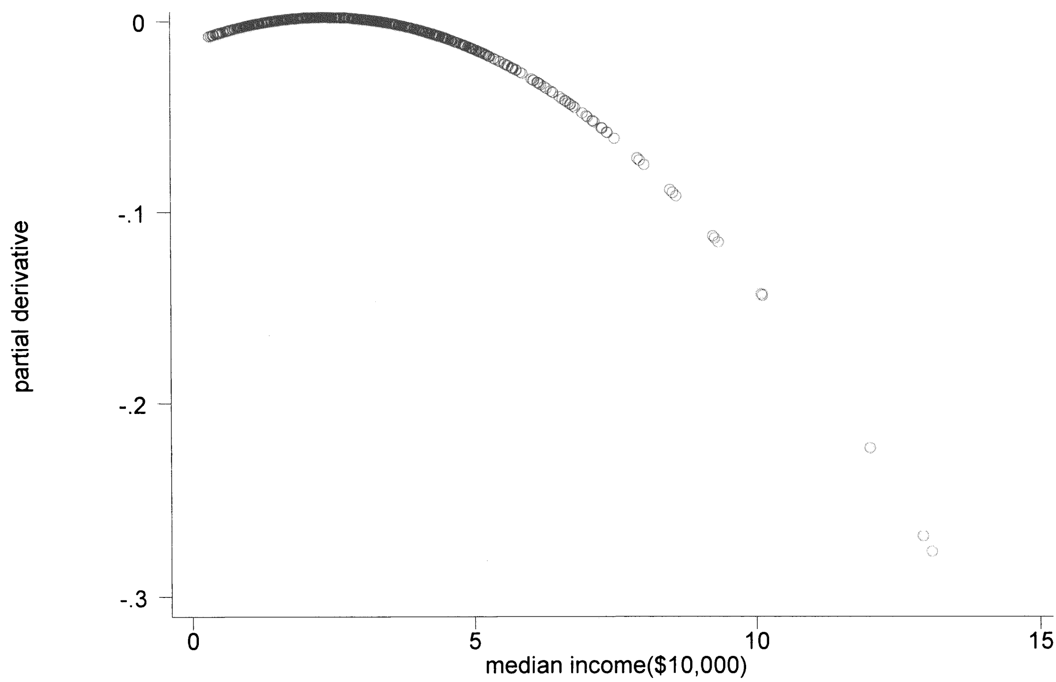

Figure 2. Partial Derivative of Property Crime Rate with Respect to Rail Access as a Function of Neighborhood Income

6. Random Effects Models

The RE models include the full set of rail access interactions (marta × povden, marta × medinc, marta × medinc^2, marta × distpoor, and marta × distpoor^2) as well as both the time-varying (X) and time-invariant (W) control variables. Table 3 reports the results from estimating total crime, property crime, and violent crime RE models using the density of crime as the dependent variable.[26] In all cases, RE is supported by the Breusch and Pagan (1980) Lagrange multiplier test for RE, a test that $\text{var}(v_i) = 0$ (see the bottom of Table 3).[27] The Hausman test results indicate that the null hypothesis of

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[26] As argued in section 4, crime density is preferred over the crime rate as the dependent variable given that we are interested in explaining the spatial distribution of crime across neighborhoods. The correct specification of a crime rate model would include different definitions of the time-invariant variables than those employed in the crime density model. However, it is worth noting that simply substituting the crime rate for the crime density in the RE models yields results that are consistent with our conclusion that rail access increases crime within the central city but reduces crime in the suburbs.

[27] As noted in section 4, the RE estimator draws on variation in the data both across and within tracts in obtaining its estimates, whereas the FE estimator relies solely on within-tract variation. A third estimator that can be used with panel data is the between estimator (BE). BE relies solely on cross-sectional variation within the data and amounts to regressing the annual mean level of crime for each tract on the annual means of the independent variables. A comparison of results between RE and BE models indicates the relative importance of between versus within-tract variation in generating the RE estimates. The more the RE estimates are based on within-tract variation in the data, the stronger the case that they reflect true causality. In the BE models, marta and its interactions with the neighborhood variables are jointly significant at the 1% level in the total, property, and violent crime equations. However, the precision of the estimated coefficients on the individual variables is substantially greater with the RE models than with the BE models. In the BE models, only one of the six rail access variables is statistically significant in any of the models: the interaction between marta and povden is significant at the 5% level in the total and violent crime models and is significant at the 10% level in the property crime model. The weaker results obtained for the BE models suggests that within-tract variation plays an important role in generating the RE estimates.

Table 3. Random Effects Models

	Total Crime Density	Property Crime Density	Violent Crime Density
marta	0.5567	0.3705	0.1338
	(1.57)[a]	(1.52)	(1.05)
marta × povden	−0.0018	−0.0015	−0.0005
	(2.25)	(2.38)	(1.92)
marta × medinc	0.0228	0.0160	0.0008
	(3.19)	(4.27)	(0.23)
marta × medinc^2	−0.0062	−0.0040	−0.0010
	(3.22)	(3.91)	(1.11)
marta × distpoor	−0.0878	−0.0592	−0.0196
	(1.45)	(1.44)	(0.88)
marta × distpoor^2	0.0033	0.0023	0.0007
	(1.31)	(1.34)	(0.76)
povden	0.1727	0.0345	0.1413
	(2.68)	(0.71)	(6.63)
medinc	−0.0230	−0.0361	0.0320
	(0.30)	(0.87)	(0.92)
medinc^2	0.0033	0.0027	−0.0008
	(0.51)	(0.80)	(0.28)
distpoor	−0.3018	−0.2627	−0.0476
	(2.91)	(3.36)	(1.37)
distpoor^2	0.0083	0.0072	0.0013
	(2.85)	(3.27)	(1.39)
jaccess	−0.0007	−0.0005	−0.0002
	(2.95)	(4.39)	(1.40)
population	−0.0028	−0.0197	0.0138
	(0.03)	(0.32)	(0.53)
blacks	0.0955	0.0721	0.0267
	(2.50)	(2.50)	(2.11)
retail	0.5915	0.5320	0.0628
	(17.79)	(20.97)	(5.79)
mfg	0.1637	0.1023	0.0618
	(5.35)	(4.37)	(6.22)
police	−10.3249	−6.7378	−3.3479
	(1.18)	(1.01)	(1.17)
males1519	−0.1970	−0.1389	−0.0744
	(0.96)	(0.89)	(1.12)
males2024	−0.1459	−0.1355	0.0081
	(0.59)	(0.72)	(0.10)
hsgrads	0.0127	0.0321	−0.0172
	(0.17)	(0.58)	(0.72)
stayers	−0.0356	−0.0165	−0.0209
	(0.063)	(0.38)	(1.13)
vacant	0.2633	0.0970	0.1653
	(7.59)	(3.66)	(14.62)
highway	0.0584	0.0493	0.0138
	(0.60)	(0.67)	(0.44)
Year 1992	0.1317	0.0634	0.0681
	(2.22)	(2.28)	(1.76)
Year 1993	0.2100	0.145	0.0973
	(2.62)	(2.98)	(1.87)

Table 3. Continued

	Total Crime Density	Property Crime Density	Violent Crime Density
Year 1994	0.1964	0.1172	0.0779
	(1.96)	(7.49)	(1.21)
Constant	2.3250	2.1540	0.1850
	(2.49)	(3.04)	(0.59)
R^2	0.890	0.888	0.878
B & P[b]	379	762	11
Hausman[c]	92	11	16

[a] Absolute value of t-statistic in parentheses.
[b] Breusch and Pagan Lagrangian multiplier test for random effects. Test statistic is distributed χ^2 with one degree of freedom.
[c] Hausman's specification test. Test statistic is distributed χ^2 with eleven degrees of freedom.

no correlation between v_i and the regressors cannot be rejected in the property and violent crime models, which supports the appropriateness of the RE estimator.[28]

The results confirm that the effect of rail transit access on neighborhood crime varies with the characteristics of the neighborhood. In the total and property crime equations, the interaction between marta and povden is statistically significant at the 5% level. This interaction is not quite significant at the 5% level in the violent crime equation. In the total and property crime equations, the interactions marta × medinc and marta × medinc^2 are significant at the 1% level. Also in these equations, the interactions marta × distpoor and marta × distpoor^2 are individually significant at just below the 10% level and are jointly significant at the 5% level. These results are consistent with the expectation that the crime effects of rail transit accessibility vary nonlinearly with the median income of the neighborhood and the neighborhood's average distance to poor people. However, in the violent crime equations none of the medinc or distpoor interactions are individually or jointly significant.[29]

Because the effect of rail access on crime varies with neighborhood variables, partial derivatives of crime density with respect to rail access were computed for combinations of three values of medinc ($10,000; $30,000; and $50,000); three value of distpoor (10, 13, and 16 miles); and three values of povden (0, 4, and 8), yielding a total of 27 combinations. The three values used for each variable roughly equal the mean of each variable and one standard deviation above and below the mean. These partial derivatives and their levels of statistical significance are reported in Table 4 for total crime density and property crime density.[30]

First note that rail access is found to increase neighborhood crime in those neighborhoods located close to poor people (distpoor = 10), except if the neighborhood is a high-income

[28] For the total crime model, the null hypothesis is rejected, but only because of a large difference between the estimated coefficients on medinc^2 between the RE and FE models. The Hausman test is based on the idea that if v_i is uncorrelated with the regressors, then the coefficients that are estimated on the time-varying variables should not statistically differ between the FE and RE models. In both of these models, medinc^2 is highly insignificant, but the difference in the coefficients is marginally significant; hence the rejection of the null hypothesis. Excluding medinc^2 from the RE model has no effect on the results and causes the Hausman test statistic to become insignificant.

[29] The weaker results for violent crime are not unexpected, since our theoretical model applies to only these violent crimes that are economically motivated.

[30] To determine whether a partial derivative is significantly different from zero, the variance of each estimate was computed using the statistical formula for the variance of a sum of random variables (Mood, Graybill, and Boes 1974, p.178). This formula accounts for the covariances between the betas retrieved from the variance-covariance matrix of the estimators.

neighborhood (medinc = $50,000).[31] These positive effects are statistically significant, except at the highest density of poverty. Among neighborhoods that are not close to the poor, rail access is found either not to have a statistically significant effect on crime or to have a negative and statistically significant effect. The absolute magnitudes of the latter effects are largest where povden and medinc are at their maximum values (8 and $50,000). These results suggest that if a neighborhood is located away from poor people, the tendencies of rail transit accessibility to cause criminals living in the neighborhood to commit their crimes elsewhere and to cause less crime by enhancing the job mobility of neighborhood residents either offset or dominate the tendency for crime to rise due to the importation of outside criminals.

The partial derivatives in Table 4 were computed for hypothetical combinations of neighborhood characteristics that are in some cases common but in other cases rare or even nonexistent among the sample of census tracts. In order to investigate transit's effects on actual neighborhoods, partial derivatives were also computed for representative neighborhoods with rail access. Four representative neighborhoods are used: central city black, central city white, suburban black, and suburban white.[32] The characteristics of each type of neighborhood can be found in Table 5. In addition to estimating partial derivatives of crime density with respect to rail access, elasticities were computed at the point of means within each type of neighborhood. Results are reported in Table 5.

For the white suburban neighborhood, all three partial derivatives are negative, and the two measuring total crime and violent crime are statistically significant at the 5% level. (The property crime partial derivative is significant at about the 15% level). The estimated elasticities suggest that the magnitude of the effects are nontrivial. For example, the elasticity of neighborhood crime density with respect to rail access is 0.70.[33]

For the black suburban neighborhood, all three partial derivatives are again negative. However, the effects are smaller than those observed for the white suburban neighborhood, and none are statistically significant.

Standing in sharp contrast to the finding that transit access reduces crime in the white suburban neighborhood are the results obtained for the white and black central city neighborhoods: all partial derivatives are positive and all are statistically significant, except for the violent crime partial derivative for the white neighborhood. Although the elasticities are substantially smaller than those estimated for the white suburban neighborhood, they are not trivial in magnitude. For example, the total crime elasticities are 0.170 and 0.149 for the black and white central city neighborhoods, respectively.

The results reported above suggest that, within the representative white suburban neighborhood with rail access, transit's negative effects on neighborhood crime (exportation of resident criminals and residents' improved job accessibility) dominate its positive effect (the importation of outside criminals), whereas within the representative central city neighborhoods the positive effect is dominant. The simple explanation for the contrasting results obtained for central city and suburban

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[31] Keep in mind that distpoor is the average distance to poor people defined over the entire seven-county Atlanta region. Hence distpoor = 10 does not mean that the poor live 10 miles away. It is generally the case that for tracts with distpoor = 10, bordering tracts have high poverty rates (in excess of 20%), which indicates many poor people live in adjacent neighborhoods.

[32] The representative neighborhood is obtained by taking a weighted average of the three neighborhood characteristics that affect rail access' effect on crime. Weights equaled the percentage of the neighborhood with rail access. A white neighborhood is defined as having more than 50% white residents. Median income is measured for the last year of the panel (1994).

[33] The elasticity is especially large for violent crime, where a 1% increase in rail access reduces the density of violent crime within the neighborhood by about 4%. The large size of this elasticity primarily reflects the fact that the base level of violent crime is low in white suburban neighborhoods.

Table 4. Implied Partial Derivatives of Neighborhood Crime Density with Respect to Rail Access

Tract Median Income	Distance to Poor	Density of Poverty	Total Crime Density	Property Crime Density
$10,000	10	0	0.024*	0.016*
		4	0.017*	0.010*
		8	0.010	0.005
	13	0	−0.012	−0.005
		4	−0.019	−0.011
		8	−0.026	−0.017
	16	0	0.011	0.013
		4	0.004	0.007
		8	−0.003	0.002
$30,000	10	0	0.021*	0.016*
		4	0.014**	0.010*
		8	0.006	0.004
	13	0	−0.015	−0.006
		4	−0.022	−0.012
		8	−0.030**	−0.017
	16	0	0.008	0.013
		4	0.001	0.007
		8	−0.007	0.001
$50,000	10	0	−0.032	−0.016
		4	−0.040	−0.022
		8	−0.047**	−0.028**
	13	0	−0.068*	−0.038*
		4	−0.076*	−0.044*
		8	−0.083*	−0.050*
	16	0	−0.045	−0.020
		4	−0.053	−0.025
		8	−0.060	−0.031

*, ** Indicates that implied partial derivative is significant at the 1% and 5% levels by a 2-tailed test, respectively.

neighborhoods comes from Table 4, which shows that the key factor in determining whether rail access will increase or decrease neighborhood crime is the neighborhood's average distance to poor people. As this distance increases, fewer outside criminals come into the neighborhood using rail transit, allowing the negative effects to overcome the positive effect.[34]

Although the relative magnitudes of the two negative effects that cause rail access to reduce crime in the suburbs cannot be determined with the available data, the most reasonable scenario is that crime declines primarily because rail access expands the employment opportunities of neighborhood residents, especially crime-prone youth who are heavily dependent on public transit.[35] That this is the case is supported by the results obtained with the variable that measures young men's proximity to jobs (jaccess): increases in jaccess are found to strongly reduce the density of neighborhood crime.

[34] Table 4 also explains the larger absolute values of the partial derivatives estimated for the white suburban neighborhood in comparison with the black suburban neighborhood. Although each neighborhood is approximately the same distance from poor people, median income is about $7,500 higher in the white neighborhood. As illustrated in Table 4, transit reduces crime more in higher income neighborhoods.

[35] A referee of this paper suggested that rail access may also reduce crime in the suburbs if fewer crime-prone families choose to live in neighborhoods containing rail access.

Table 5. The Effect of Rail Access on Representative Neighborhoods

	Total Crime Density	Property Crime Density	Violent Crime Density
Black city[a]	0.016[e]	0.010	0.005
	(3.59)[f]	(3.06)	(3.24)
	[0.170][g]	[0.147]	[0.189]
White city[b]	0.012	0.010	0.001
	(2.14)	(2.67)	(0.36)
	[0.149]	[0.158]	[0.043]
Black suburbs[c]	−0.016	−0.006	−0.006
	(1.22)	(0.74)	(1.25)
	[0.453]	[0.229]	[0.81]
White suburbs[d]	−0.027	−0.013	−0.010
	(2.03)	(1.49)	(1.99)
	[0.696]	[0.359]	[3.913]

[a] Black city: medinc = $14,896, distpoor = 10.16 miles, povden = 5.02.
[b] White city: medinc = $30,526, distpoor = 10.27 miles, povden = 1.25.
[c] Black suburbs: medinc = $28,705, distpoor = 13.26 miles, povden = 0.89.
[d] White suburbs: medinc = $36,168, distpoor = 12.92 miles, povden = 0.62.
[e] Implied partial derivative.
[f] Absolute value of t-statistic in parentheses.
[g] Elasticity evaluated at the means for the area in brackets.

Hence regardless of whether job opportunities are improved by reducing the distance to jobs or by reducing the time it takes to get to jobs, the effect is to increase the opportunity cost of crime among young offenders.

There is, however, an alternative explanation for the suburban results: more police resources may be allocated to those neighborhoods with rail access, which may cause crime to be lower within these neighborhoods. Allocating more resources to transit neighborhoods may be law enforcement officials' response to neighborhood residents' concerns over station-induced crime. To investigate this hypothesis, tract arrest rates were computed for each of the years of the crime panel for the suburban portion of the sample (i.e., DeKalb County).[36] The tract arrest rate (AR), defined as the number of arrests for crimes committed in the neighborhood divided by the total number of reported crimes committed in the neighborhood, was regressed on the lagged value of the tract crime density (CD) and the lagged value of the percentage of the tract within a quarter mile of a transit station (marta). The results are as follows (t-statistics in parentheses):

$$\begin{array}{ll} AR_t = 0.230 + \underset{(4.73)}{0.115}\ CD_{t-1} + \underset{(1.24)}{0.004}\ \text{marta}_{t-1} & R^2 = 0.080 \\ & n = 276 \\ & F(2,273) = 12. \end{array}$$

Although marta has the expected positive sign, its estimated coefficient is not statistically significant. The results therefore provide little support for the alternative explanation for the suburban results.

Finally, there are the results obtained with the control variables. Six variables are remarkable in their effects. The densities of poverty, black population, retail employment, manufacturing employment, and vacant housing all have positive and statistical significant effects on total neighborhood crime, whereas the job accessibility of young men significantly reduces crime. One anomalous result

[36] The data used to compute arrest rates were provided by the DeKalb County Office of Information Systems.

is that neither youth density variable (males1519 and males2024) is significant in any of the crime models, despite the fact that youth are known to be crime prone. An explanation for the insignificance of the youth variables is that these variables are time-invariant and their variation across tracts is limited.[37]

7. Conclusion

The consensus opinion among transportation planners is that rail transit must play a major role in reducing air pollution and automobile congestion within urban areas. The favored approach is to build more stations and to encourage transit-oriented development around existing stations. The success of these policies will in part depend upon transit's effect on neighborhood crime. On this issue there has been much speculation but little empirical evidence.

The relationship between rail access and neighborhood crime is more complex than commonly recognized. Although the opening of a rail station may increase access to the neighborhood by outside criminals, it may also induce criminals living within the neighborhood to commit their crimes elsewhere. In addition, the station may increase the job accessibility of crime-prone neighborhood residents, causing them to choose legitimate work, rather than crime.

The results obtained from the RE models suggest that rail access does increase crime within those neighborhoods that are both close to poor people and are not high-income. Because poor people are concentrated within the central city, rail access is found to increase crime within both the representative white and black central city neighborhood. This conclusion can also be drawn from the results obtained from the FE models, which show that at the income levels that typify central city neighborhoods, rail access has a positive effect on crime. Efforts to attract population and employment to station areas located within the central city may therefore be frustrated by higher crime unless greater deterrence is provided. On the other hand, there is no evidence from either the random or FE models that suburban residents should fear that crime will rise in their neighborhood if rail lines are extended beyond central city boundaries. It is ironic that rail access is actually found to reduce crime in the representative white suburban neighborhood, because most of the opposition to rail transit has come from white suburban residents. This opposition, however, may only superficially have to do with concerns over crime. The real motivation may be racial bigotry (Bayor 2000).

The theory presented in this paper explains the important role that distance to the poor plays in transit's effect on neighborhood crime as the result of travel costs. The farther the neighborhood is located from a criminal, the lower is his expected payoff net of the costs of travel. Hence, even after a neighborhood obtains a rail station, if the criminal's trip to the neighborhood is lengthy he may find that net returns are higher closer to home. However, it was also noted that the distance to the poor effect may reflect the criminal's expected probability of apprehension. The criminal may feel comfortable using rail transit to get to a nearby neighborhood that he has some familiarity with, but he may be reluctant to take transit to a distant neighborhood because it is not part of his "mental map," and he therefore has less confidence in his ability to succeed in his crime. If it is the unfamiliarity of the distant neighborhood, rather than the travel costs, that deters the criminal, then distance may become less of a barrier over time. That is, the criminal's access to the neighborhood by rail transit may eventually expand his mental map to include the neighborhood. This suggests that an issue for

[37] For both variables the coefficient of variation is equal to one.

future research would be to investigate how transit's effect on neighborhood crime might vary over time. A suburban neighborhood with rail access may be safe today but not indefinitely into the future.

The results presented in this paper are based on the experience of a single metropolitan area—Atlanta, Georgia. Care should be taken in generalizing the conclusions of this study to other areas. However, the three factors that influence transit's effect on neighborhood crime exist within all metropolitan areas. Hence transit's effect on neighborhood crime will vary across neighborhoods, with neighborhoods closer to poor people more likely to experience an increase in crime from transit access. From a policy perspective, a relatively greater proportion of police resources should be allocated to these neighborhoods, especially within those metropolitan areas where transit-oriented development is a high priority in the battle against urban sprawl.

A final caveat also points to a suggestion for future research. Although this study estimated both FE and RE models, results from the latter models received greater attention because they permitted a full investigation of the variation in effects that rail access has on neighborhood crime. However, causality is more difficult to establish when using an RE model. This is acknowledged in the present study, although the consistency in the results between the RE and FE models, the results from Hausman tests, and the fact that the RE estimates rely heavily on within-tract variation in the data suggest that my findings reflect the causal relationships hypothesized by our theoretical model. Nevertheless, the use of longer crime panels that would allow the estimation of more complex FE models is recommended in future investigations of the effects of rail transit access on neighborhood crime.

Appendix. Means (Standard Deviations)

	Full Sample	Tracts with Rail Access	Tracts without Rail Access
Total crime density	1.20	2.12	0.76
	(2.12)	(3.06)	(1.26)
Property crime density	0.79	1.40	0.50
	(1.44)	(2.23)	(0.65)
Violent crime density	0.41	0.72	0.26
	(0.93)	(1.25)	(0.67)
Total crime rate	0.244	0.514	0.115
	(1.34)	(2.33)	(0.102)
Property crime rate	0.187	0.406	0.082
	(1.15)	(2.01)	(0.070)
Violent crime rate	0.057	0.108	0.033
	(0.193)	(0.328)	(0.041)
marta	6.08	18.7	0
	(15.17)	(21.8)	
povden	1.74	2.97	1.15
	(3.77)	(5.72)	(2.07)
medinc	31,102	22,064	35,435
	(18,225)	(11,953)	(19,112)
distpoor	12.63	10.92	13.44
	(3.20)	(1.28)	(3.50)
jaccess	−9.10	−24.42	−1.75
	(163)	(182)	(153)
population	6.33	8.49	5.37
	(5.29)	(7.05)	(4.27)
blacks	4.24	6.26	3.28
	(5.53)	(7.36)	(4.04)
retail	0.73	1.28	0.47
	(1.84)	(2.98)	(0.75)
mfg	0.52	0.94	0.27
	(1.68)	(2.71)	(0.56)
police	0.01	0.02	0.01
	(0.01)	(0.01)	(0.00)
males1519	0.21	0.26	0.19
	(0.46)	(0.37)	(0.50)
males2024	0.26	0.36	0.21
	(0.37)	(0.46)	(0.30)
hsgrads	4.29	5.23	3.84
	(2.89)	(2.94)	(2.76)
stayers	2.69	3.52	2.30
	(1.97)	(2.33)	(1.63)
vacant	0.51	0.64	0.45
	(1.75)	(0.84)	(2.05)
highway	0.66	0.71	0.63
	(0.47)	(0.45)	(0.48)
observations	824	267	557

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