Externality Effects on Residential Property Values: The Example of Noise Disamenities

ARTICLE *in* GROWTH AND CHANGE · SEPTEMBER 2006

Impact Factor: 1.05 · DOI: 10.1111/j.1468-2257.2006.00332.x · Source: RePEc

David Clark
Marquette University

Growth and Change
Vol. 37 No. 3 (September 2006), pp. 460–488

Externality Effects on Residential Property Values: The Example of Noise Disamenities

DAVID E. CLARK

ABSTRACT Studies conducted by the Federal Railroad Administration in the 1990s reveal that train whistle bans lead to higher accident rates at train crossings. However, advocates of these bans argue that they eliminate noise externalities that have a detrimental effect on residential home values. To assess this latter claim, an event study is conducted and hedonic models are estimated for three different areas in which Conrail unilaterally began ignoring local whistle bans. While the findings consistently show that proximity to rail lines has a negative and statistically important influence on home values, there is little evidence that the Conrail decision had any permanent and appreciable influence on the housing values in these communities. In two of the three study areas, there is no statistically significant impact of the Conrail action, and in the third area, the effects are found to be temporary in duration.

Introduction

In 1992 and 1995, the Federal Railroad Administration (FRA) issued the findings of two separate studies (FRA, September 1992; FRA, April 1995) on the influence of train whistle bans on fatal accidents. The findings revealed substantially lower accident rates at train crossings where whistles are blown as compared to areas where no whistles are blown. In addition to the societal costs resulting from the loss of human life, accidents are also costly to railroads in terms of service disruptions as well as track and crossing repairs. In October 1991, Conrail unilaterally decided to ignore the whistle bans in the cities in which it operates. Critics of this decision contended that residential property markets were detrimentally impacted by Conrail's action. A number of studies in the research literature investigate the influence of noise on annoyance levels of residents. For example, Osada (1991) evaluates community reaction to aircraft noise near Japanese airports. Using

David Clark is an associate professor in the Department of Economics at Marquette University in Milwaukee, Wisconsin. His email address is: david.clark@marquette.edu. *An earlier version of this research was supported by the Federal Railroad Administration (FRA) under interagency agreement through U.S. Department of Energy contract W-31-109-Eng-38. The preliminary research for this article was conducted while the author was a Special Term Appointment consultant working for Argonne National Laboratory. The opinions expressed in the article are those of the author and do not represent the opinions of FRA or Argonne National Laboratory. The author would like to thank the editor and two anonymous referees for very helpful comments on an earlier draft of the article.*

Submitted April 2004; revised January 2006; accepted March 2006.

discriminant analysis, I find that annoyance rates are highly related to noise levels and they depend on personal characteristics of the respondent. In addition, Osada compares the findings on airport noise with that of other studies evaluating road traffic and train noise. Similar responses to noise are found across various sources and different time periods considered. Another study by Björkman (1991) uses a dose-response model to investigate how road-traffic noise levels and event frequency influence annoyance levels. Björkman concludes that the number of noise events increases annoyance rates up to a point, beyond which there is no additional reaction to additional events. It was also determined that annoyance depends on the level of noise, and that this effect is independent of the frequency of noise events. Sörensen and Hammar (1983) find similar results when evaluating train noise. Specifically, they find that the number of noise events and the level of noise both influence the percent of residents who report that they are very annoyed. Residents report no annoyance for less than fifty trains per twenty-four-hour period. Above the fifty-train threshold, the level of annoyance depends on noise levels. These results are similar to a study of aircraft noise by Rylander, et al. (1980). Finally, a recent study by Multer and Rapoza (1998) evaluates community impacts from wayside horns (i.e., horns that are placed in a fixed location as opposed to a moving train) versus train horns. They found lower levels of reported annoyance for wayside horns, which were approximately 13 dB quieter than train horns. In addition, the wayside horn was found to have a severe impact for residents within 100 feet of the track, whereas severe impacts were found for train horns within 1,000 feet of the track.

Although survey research is important in measuring attitudes towards noxious activity, stated levels of annoyance do not necessarily translate into actual economic impacts. For example, Metz (1994) shows that stated preferences on aversion to nuclear waste are inconsistent with actual behavior. That is, individuals typically report that a minimum safe distance for storage of nuclear waste is in excess of the actual distance they live from waste. An alternative approach to valuing local externalities is to examine their impact on residential property values.[1] Under certain circumstances, these impacts can be considered implicit prices for amenities. In a recent study, Strand and Vagnes (2001) find that properties in Oslo, Norway, selling within 100 meters of rail lines are detrimentally impacted. They find that a doubling of the distance within the 100-meter buffer area increases housing values 10 percent. However, this study does not distinguish between proximity to rail lines, and proximity to rail crossings where whistles are blown. Another recent study by Simons and El Jaouhari (2004) evaluated activity levels on railroad tracks in Cuyahoga County in Ohio (a metropolitan county in Cleveland) in the late 1990s and found significant detrimental effects from proximity to freight tracks ranging from 2 percent to 4 percent of the average residential sales price. In a related study, El Jaouhari and Simons (2002) show that proximity to a rapid transit station in Cuyahoga County actually increases property values by 9 percent to 14 percent of the average price for those properties between 750 and 1,000 feet of a rail station. Interestingly, they also find evidence of a nuisance effect for stations. Specifically, households living too close to a rapid transit station (i.e., less than 750 feet) do not experience a significant positive benefit, and the premium for those between 750 and

1,000 feet is diminished by higher levels of customers at the station. In the current study, the author investigates the extent to which the action taken by Conrail to ignore whistle bans at grade crossings influenced residential property sales prices in the vicinity of railroad crossings in two different cities in Ohio and one city in Massachusetts.

Theoretical Overview of Hedonic Model

The hedonic model treats a unit of housing as a heterogeneous bundle of characteristics. These characteristics include different structural features of the housing unit (e.g., numbers of bedrooms and bathrooms, interior square footage, etc.) as well as features of the neighborhood (e.g., locational attributes such as poverty rates, racial and ethnic characteristics, average commute time, proximity to rail lines, etc.). One advantage of this modeling approach is that it allows one to examine the *ceteris paribus* influence that a particular attribute has on local housing prices. That is, holding constant the impact of structural characteristics of the home as well as other neighborhood attributes, one can examine the independent influence on the sale price of the property of a rail crossing or a decision to ignore a ban on train whistles. The theory, which has its foundations in the works of Lancaster (1966), Rosen (1974) and others (Freeman 1979; Palmquist 1984; Brown and Rosen 1982, Diamond and Smith 1985; Epple 1987; Bartik 1987), has been extensively developed in the literature; hence, it will only be briefly reviewed here. Assuming 1) perfect information about the bundle of attributes embodied in each house, 2) zero transactions costs in market trades of bundles, and 3) a continuous offering of attributes, the market price of a house can be represented as p(z), where $z = z_1, z_2, \ldots, z_n$ is a vector of structural and neighborhood attributes. The hedonic price function p(z) represents a reduced-form equation, which embodies both supply and demand influences in the housing market. The implicit price of attribute j is then given by the partial derivative of p(z) with respect to attribute j, or $p_j(z) = \partial p/\partial z_j$.[2] That is, assuming the above conditions are satisfied, $p_j(z)$ represents the independent influence of attribute z_j on the housing price, holding constant the influence of other attributes. The equilibrium price function, p(z), is assumed to be a nonlinear function because the cost of arbitrage activity that repackages bundles of attributes once a house is built is assumed to be prohibitive.

Many studies have applied the hedonic methodology to value neighborhood externalities and local public goods (Haurin and Brasington 1996; McDougall 1976). Applying this model to a train whistle policy change can shed light on the impact of noxious activity on residential property markets and the dynamic adjustment of property markets after such an event. For example, Kiel and McClain (1995) show that the implicit price, p_j, associated with an incinerator project varied as the project moved from the rumor stage to actual operation of the facility. Thus, it is possible that the influence of the policy change on train whistles has an immediate short-run effect and smaller long-run impacts. Indeed, Galster (1986) argues that even relatively significant events such as the Three Mile Island nuclear accident may have relatively minor long-term property value impacts. This is because the residents most sensitive to the presence of a nuclear power plant had long since moved from the vicinity of the plant when the accident occurred. Those who lived in the region at the time of the accident were by definition those who were least concerned with the risks associated with the facility. The same phenomenon may be at work as one considers the influence of whistle bans. Specifically, households who are most sensitive to train noise are unlikely to live close to an established rail line. Hence, long-run adjustments in the composition of local residents may serve to mitigate any property value impacts associated with the policy change. Furthermore, even though the Conrail crossings did not have whistle activity before October 1991, local residents may believe there to be some probability of a policy change in the future. To the extent that they consider this possibility when determining their offer price for the property, this would further diminish any measured housing price impact associated with the policy change. To test whether a change in train whistle activity influences residential home sale prices, hedonic models are estimated for properties selling in three communities. The sales took place both before and after the whistle ban was ignored by Conrail, permitting the development of an event study. The policy change is then evaluated to see whether its impact on properties near rail crossings was temporary or permanent.

Empirical Model

Description of study areas. The study estimates a hedonic model using a sample of properties that sold in three counties; two in Ohio, and one in Massachusetts. The Ohio counties include Butler County in the southwestern part of the state, which contains Middletown, and Trumbull County in northeastern Ohio, which contains Niles. The Massachusetts data include transactions from Middlesex County, which contains Framingham. The choice of study areas was dictated by data availability and by two primary requirements. First, the data needed to span the period of the Conrail decision, and second, whistle bans needed to be in place prior to the Conrail decision. The data sets were obtained from two different sources: The Ohio data were obtained from Dataquick and cover the period January 1988 to January 1997. Of the 4,725 properties sold in Butler County, 3,733 or 65.2 percent sold after the ban was ignored, whereas 61.1 percent of the 4,182 properties in Trumbull County sold after the Conrail action. The Massachusetts data were obtained from Experían and cover the period January 1986 to July 1997. Of the 2,718 observations in Middlesex County, 68.0 percent sold after the Conrail action. All property data are geocoded to the street address of the house,[3] which permits matching of the property to the salient locational attributes in the vicinity of the property. The demographic characteristics of each county are described in Table 1.

Of the three geographic regions, Middlesex County, which is a western suburb of Boston, is the most densely populated. It also has the highest median family income, as well as the highest home values and rents. In Ohio, Butler County is more affluent than Trumbull. All three regions are predominantly white, although there are some differences in minority compositions across the three areas. Minority populations in the Ohio counties are predominantly black, whereas Middlesex has higher concentrations of Asian and Hispanic residents.

TABLE 1. DEMOGRAPHIC CHARACTERISTICS OF STUDY AREAS.

Demographic characteristic	Butler County Ohio	Trumbull County Ohio	Middlesex County Massachusetts
Median family income	$38,673	$33,313	$52,112
Median housing value	$72,500	$53,200	$192,200
Median gross rent	$415	$346	$671
Percent owner occupied	69.22	73.09	59.63
Population (persons)	291,479	227,813	1,398,468
Population density (persons/square mile)	154.12	91.41	419.69
% Black	4.50	6.68	2.87
% Asian	0.91	0.42	3.70
% White	94.31	92.58	92.05
% Hispanic	0.50	0.64	3.39

Source: County data, 1990 U.S. Census of Population and Housing.

Description of model. To avoid misspecification biases and mitigate problems associated with unmeasured spatially correlated influences, the author controls for numerous housing influences in the model. These variables can be assumed to fall into one of four broad categories; *Structural, Neighborhood, Time Sold,* and *Railroad.* A semilog specification is chosen,[4] and the model is specified by equation (1).

$$\ln RPRICE = f\,(\textit{Structure}, \textit{Neighborhood}, \textit{Time Sold}, \textit{Railroad}) \tag{1}$$

All variable definitions, and data sources, are reported in Table 2. The dependent variable lnRPRICE is the log of real sale price of housing and is deflated by the housing component of the Consumer Price Index (CPI) for the month in which the property sold.

Categories of independent variables. The first category of variables, *Structure,* represents structural features of the house. The variables in this category differ slightly between the Ohio and Massachusetts specifications. These include the number of bedrooms, bathrooms (bathrooms for OH; half baths and full baths for MA) and other rooms; the number of fireplaces; the age of the structure; the size of the lot on which the structure is located; and the square footage of the structure itself and the garage (Ohio properties only). Finally, the presence of a pool (Ohio properties only) and the number of stories of the property are also controlled. Note that the age of the house and the measures of building and garage area and lot size are included in both linear and quadratic forms so as to account for potential nonlinear effects of these variables on home sale prices.[5] One would expect that structural features that increase the housing services generated by a property increase the sales price.

TABLE 2. VARIABLE NAME, DEFINITION, AND DATA SOURCE.

Variable Name	Definition	Source
Dependent Variable and Variables in the *Structural* Category		
Real price	Real sale price of the property (1990 dollars)	Dataquick or Experían nominal price divided by the national CPI for housing
Age house	Age of the house in years.	Dataquick or Experían
Bathrooms (OH) Half baths (MA) Full baths (MA)	Sum of full and half baths, where each full bath = 1 and each half bath = 0.5.	Dataquick or Experían
Bedrooms	Number of bedrooms in house	Dataquick or Experían
Other rooms	Total rooms minus number of bedrooms	Dataquick or Experían
Fireplace	Number of fireplaces in the house	Dataquick or Experían
Number of stories	Number of stories in the property	Dataquick or Experían
Pool	1 = Presence of a pool, 0 = otherwise. (OH only)	Dataquick
Building area	Structure area in square feet.	Dataquick or Experían
Garage area	Garage area in square feet. (OH only)	Dataquick
Lot area	Lot area in square feet.	Dataquick or Experían
Variables in the *Neighborhood* Category		
Airport 3 miles;	1 = Property is within three miles from the edge of an airport, 0 = otherwise.	FAA geocoded airport locations
Distance	Distance in miles to airport if within three-mile buffer.	
Highway quarter mile;	1 = Property is within 0.25 mile of interstate highway, 0 = otherwise	ESRI Data and Maps
Distance	Distance in feet to highway if within 0.25 mile buffer.	
Air quality monitor distance	Distance to closest EPA air quality monitor in miles.	LandView III database

TABLE 2. (CONTINUED)

Variable Name	Definition	Source
Toxic Release Inventory, three miles;	1 = Property is within three miles of a TRI facility, 0 = otherwise.	LandView III database
Distance	Distance in miles to facility if within three-mile buffer.	
Superfund, three miles;	1 = Property within three miles of Superfund site, 0 = otherwise.	Landview III database
distance	Distance in miles to Superfund site if within three-mile buffer.	
Power plant 3 miles;	1 = non-nuclear power plant within three miles, 0 = otherwise.	Landview III database
distance	Distance in miles to plant if within three-mile buffer.	
% owner occupied	Percent of the housing units in the census block group that are owner occupied.	1990 Census of Population and Housing
% Occupied units	Percent of the housing units in the census block group that are occupied	1990 Census of Pop. and Housing
% Asian	Percent of the persons in the census block group who are Asian/Pacific Islander	1990 Census of Pop. and Housing
% black	Percent of the persons in the census block group who are black	1990 Census of Pop. and Housing
% Hispanic	Percent of the persons in the census block group who are Hispanic	1990 Census of Pop. and Housing
Median household income	Median household income in the census block group	1990 Census of Pop. and Housing
Commute time	Average commuting time in the census block group	1990 Census of Pop. and Housing
Lake/River	1 = Lake or river within 3 miles of the property	ESRI Data and Maps.
Tax rate	Imputed property tax rate	Dataquick or Experían

Median year built	The median year in which the housing units in the census block group were built	1990 Census of Pop. and Housing
Variables in the *Railroad* Category		
Line impact area (LIA)	1 = Rail line within 1,000 feet of the property, 0 = otherwise.	Computed from FRA crossing database.
Distance from rail line	Distance of the property rail line in miles.	Computed from FRA database
Crossing impact area (CIA)	1 = Rail crossing within 2,320 feet of the property, 0 = otherwise.	Computed from FRA database
Severe impact area	1 = Rail crossing within 1,000 feet of the property, 0 = otherwise.	Computed from FRA database
Moderate impact area	1 = Rail crossing between 1,000 and 2,320 feet of the property, 0 = otherwise.	Computed from FRA database
Distance from rail crossing	Distance of the property from the rail crossing in miles.	Computed from FRA database
Ignore	1 = property sold more than 45 days after the decision by Conrail to ignore the whistle ban, 0 = otherwise.	Computed from FRA database
Days since	The number of days since the whistle ban was ignored.	Computed from FRA database

Neighborhood and time trend variables. Both Dataquick and Experían data are geocoded to the property address thereby permitting a wide range of neighborhood characteristics to be precisely matched to each property. ArcView is used to map each property to a census block group and the characteristics of that block group are then assigned to the property. Among the characteristics included are the percent of the houses that are occupied (*%occupied*), the percent of the occupied units that are owner occupied (*%owner occupied*), and the racial and ethnic mix of the block group (*%Asian, %Black,* and *%Hispanic*). Also included in this set of demographic controls is the median household income of the block group (*median HH income*). Finally, the age of housing in the neighborhood (*median year built*) is included to proxy the age of the neighborhood, and the average commute time within the block group (*commute time*) is included to account for enhancements to housing prices that result from reduced travel times. Also included is *population density*, which captures both amenities (e.g., variety in cultural amenities) and disamenities (e.g., congestion, noise, crime, etc.) associated with more densely populated neighborhoods.

Neighborhoods with relatively higher rates of occupied units, owner occupancy, and median income are expected to exhibit higher sale prices since the sample is comprised of single-family homes. In addition, the urban location model predicts that lower commute times should result in higher sale prices, *ceteris paribus*. Finally, the expected impact of the racial and ethnic variables is unknown *a priori* because the race or ethnicity of the buyers, which may proxy individual preferences, are unknown.

ArcView is also used to determine how close each property is to various types of noxious activity, specifically, activity related to the proximity to interstate highways and airports. Because a primary goal of this study is to measure the influence of noise on residential property markets, I measure the airport gradient (i.e., the price–distance relationship) for distances of up to three miles from the airport and distances up to 0.25 miles for highways. These distances are believed to reflect the feasible range for noise impacts associated with these activities, and hence noise levels outside these ranges are assumed to be too low to influence property markets. Air quality in the neighborhood is proxied by distance from the nearest EPA air quality monitor (*air quality monitor distance*). Since monitors are not uniformly dispersed throughout metropolitan areas, but rather are placed in areas that are more likely to have elevated readings, one expects properties located at greater distances from a monitor to experience higher air quality. Proximity to several different types of potentially hazardous activity were modeled with two separate variables. Specifically, a dummy variable was included for a three-mile range around the property, and then distance from the site is interacted with the dummy variable to derive a distance gradient. This was done for Superfund sites in the community,[6] the presence of production facilities on the Toxic Release Inventory,[7] and also proximity to nonnuclear power plants to proxy emissions associated with these facilities (*power plant 3 miles)*. Note that the impact of power plants may be ambiguous. This is because there are potential beneficial impacts (e.g., tax subsidies from the utility, employment effects) as well as detrimental effects (e.g., pollution, congestion) from the facility.[8]

Next, proximity to streams, lakes, and rivers (*lake/river 3 mile*) is included to proxy access to aesthetic and recreational amenities as well as flooding risks. The *property tax rate* for the residence is included to measure the local property tax burden and dummy variables for the school district to account for housing price differentials related to variations in school quality. The data set also contains information about the political jurisdiction in which each dwelling lies. To account for amenities and disamenities as well as public goods and services associated with the community, dummy variables for the political jurisdiction and the specific school district are also included (*city dummy*).

Variables in the *Time Sold* category include dummy variables for the year in which the property sold. This should control for the influence of long-run trends in housing prices, as well as factors related to the business cycle. The omitted year is 1987 for the Ohio data and 1986 for Massachusetts. In addition, seasonal dummy variables are included to account for whether the property was sold in the spring, summer, fall, or winter, with winter being the omitted dummy variable. There are no sign expectations in any of the time-related variables because both supply and demand for housing will change during each period.

Railroad variables. To account for the influence of railroad noise, several different measures are included in the *Railroad* category. To account for whistle noise, the distance of the property to the closest rail crossing is measured. Rail crossings that are maintained by Conrail are distinguished from other crossing data. Note that a crossing is classified as a Conrail crossing if Conrail maintains it, or if any Conrail trains travel through the crossing. Multer and Rapoza (1998) report that locomotive engineers begin sounding their horn approximately 1,320 feet (i.e., a quarter mile) from the highway-railroad grade crossing. In addition, they report that the impact or severe impact zone for train whistles is, at most, 1,000 feet from the train, so an operational definition of an impact zone of properties within 2,320 feet of a rail crossing is adopted. The impact zone is split into moderate and high impact ranges by defining the area within 1,000 feet as severe impact and the area 1,000 to 2,320 as a moderate impact zone.

In general, homes in Butler County are closer to rail crossings than in the other study areas. Specifically, 23.9 percent of the properties in this sample fall within 2,320 feet of Conrail crossings in Butler County whereas 8.5 percent and 2.7 percent are within that distance of Conrail crossings for Trumbull and Middlesex Counties, respectively. Likewise, the properties in Butler are also closer to crossings of other rail companies on average (i.e., 7.2 percent are within 2,320 feet for Butler County; 1.5 percent are within that impact zone for Trumbull County and 1.6 percent are within that distance for Middlesex County). Noise and vibration may also result from proximity to rail lines, even if the property is not close to a rail crossing. Thus, it is important to control for proximity to both rail lines and rail crossings. A 1,000-foot buffer zone (*Line impact area,* or *LIA*) is constructed around each rail line, and again, the line is classified by the rail company. It is assumed that noise and vibration that is unrelated to whistle noise will dissipate within 1,000 feet. As with the crossing data, Butler properties tend to be closer than those in other counties to rail lines with 17.9 percent within 1,000 feet of Conrail lines, and 7.8 percent within that distance of other lines. This is in contrast to the findings for Trumbull County (5.7 percent for Conrail lines and 4.8 percent for other lines) and Middlesex County (7.2 percent for Conrail lines and 1.3 percent for other lines).

Two different specifications are examined for each of the three geographic regions. The first specification uses dummy variables to distinguish between impacts in the moderate and severe impact areas. This is given by equation (2) below.

$$\ln(rprice) = \beta_0 + \beta_1 * \text{Control} + \beta_2 * LIA_j + \beta_3 * XIA_k + \beta_4 * XIA_{k:Conrail} * Ignore + \beta_5 * XIA_{k:Conrail} * Ignore * Days\ since \tag{2}$$

where: ln(*rprice*) = the log of the real sales price

Control = Vector of control variables, and β_1 a vector of coefficients on those variables;

LIA_j = Line impact area (i.e., within 1,000 feet of the rail line) for j = Conrail, Other;

XIA_k = Crossing impact area for k = moderate, severe;

Ignore = A zero-one dummy variable that takes on a value of one if the property sold at least 45 days after the date when Conrail began ignoring the whistle ban.

Days since = the number of days that have passed since 45 days after the Conrail action.

Properties that closed within forty-five days of the Conrail action would not have been influenced by the action for two reasons. First, Conrail did not provide any advanced warning of its decision to discontinue observing the whistle ban. Furthermore, it typically takes four to six weeks to close on a property. Hence, properties selling within forty-five days of the Conrail action would have had an accepted offer before the action to ignore the bans. While it may be possible for the buyer to withdraw the offer once Conrail began blowing their whistles, those transactions would not take place within the forty-five-day period subsequent to the action. The coefficient on *LIA*, (β_2) is expected to be negative if proximity to a train line represents a local disamenity. The coefficients on the crossing dummy variables (i.e., estimates of β_3) would also be expected to be negative, with the coefficient on the XIA_{severe} anticipated to be more negative than the coefficient on $XIA_{moderate}$. If the action by Conrail is detrimental to property values, then the estimate of β_4 should be negative and statistically significant. That is, ignoring the whistle ban would significantly reduce sale prices on property below the baseline level established by the estimates of β_3. Finally, the last term is designed to capture temporal differences in property value impacts, such as those identified by Kiel and McClain (1995). If negative impacts grow over time (i.e., the area is stigmatized), this coefficient could be negative, implying continued declines in property prices after the action. On the other hand, if negative impacts are only temporary, then one would expect a positive estimate of β_5.

The second specification estimates continuous distance gradients (i.e., price–distance relationships) for the entire impact area rather than dividing the crossing impact area (CIA) into moderate and severe ranges with separate dummy variables. It then investigates the influence of the Conrail action on the slope of the gradient. The model is given by equation (3).

$$\begin{aligned} \ln(rprice) = {} & \beta_0 + \beta_1 * \text{Control} + \beta_2 * LIA_j + \beta_3 * LIA_j * Distance_j + \\ & \beta_4 * XIA_j + \beta_5 * XIA_j * Distance_j + \\ & \beta_6 * XIA_{Conrail} * Distance_{Conrail} * Ignore + \\ & \beta_7 * XIA_{Conrail} * Distance_{Conrail} * Ignore * Days\ since \end{aligned} \tag{3}$$

where ln(*rprice*), Control, *LIA, Ignore* and *Days since* are defined as before.

XIA_j = 2320 foot radius crossing impact area for j = Conrail, Other crossing.

$Distance_j$ = distance from property to rail crossing, or rail line j

The estimate of the coefficient on $LIA_j*Distance_j$ (i.e., β_3) represents the rate at which housing prices change with distance from the rail line. If proximity to rail lines is undesirable, then it would be expected that $\beta_2 < 0$ and $\beta_3 > 0$. That is, prices would be expected to be lower for homes selling within the impact area (i.e., $\beta_2 < 0$) but they would rise with greater distance from the line (i.e., $\beta_3 > 0$). Similarly, the coefficient estimate on XIA_j (i.e., β_4) represents the baseline impact associated with residing within the impact area. In addition, as distance from the crossing increases, property prices should rise if being close to the crossing is undesirable. Hence, the estimate of β_5 is expected to be positive. If the Conrail decision to ignore the ban increases the premium for distance from the crossing, then the estimate of β_6 would be positive, and the expected sign on β_7 depends on whether property impacts decline, or are exacerbated, over time.

Empirical Findings

Separate regressions are estimated for each of the three geographic regions, and a White test reveals evidence of heteroskedasticity in all regressions. White's correction technique is used to generate consistent estimates of standard errors (White 1980). The findings on the two specifications are reported in Tables 3 and 4, respectively. Because the coefficients and the *t*-scores on control variables differ very little between the specifications, they are only discussed for the first specification.[9] In addition, the discussion will focus on coefficients that are statistically significant in a two-tailed test at the 90 percent level of confidence or higher. The regression models explained 64.3 percent of the variation in the log of real sale prices in Butler County; 61.7 percent of the variation in Trumbull County; and 48.8 percent in Middlesex County. While the model specifications are nearly identical, the fit in Middlesex County is significantly lower. Recall that the population density is significantly higher in the Middlesex as compared to the other counties, and this may imply that unmeasured neighborhood externalities are more prominent in that county.

Structural variables. Most structural characteristics are significant and of the anticipated sign. The influence of age on housing price is generally negative although not all coefficients are significant. Treating the coefficients as point estimates, the net effect of the linear and quadratic coefficients is negative in the relevant range of the data for all counties. Holding square footage constant, additional bedrooms, bathrooms, and other rooms

TABLE 3. HEDONIC REGRESSION EXAMINING EFFECT OF CONRAIL ACTION ON IMPACT ZONES.

Variable	Butler County		Trumbull County		Middlesex County	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
a. *Intercept*	3.03453	1.616	9.509976	5.687***	349.4428	1.524
b. *Structural Characteristics*						
Age house	–0.003341	–3.186***	–2.96E-04	–0.371[m]	–0.175215	–1.513[m]
Age house squared	–5.18E-06	–0.601[m]	–4.42E-05	–5.723***	2.50E-05	3.768***
Bedrooms	0.054248	4.905***	0.048357	4.544***	0.023086	1.471
Bathrooms (OH) Full bath (MA)	0.016989	1.362	0.102802	6.996***	0.043785	2.006**
Half bath (MA)					0.075038	4.484***
Other rooms	0.024233	3.595***	0.033494	4.084***	0.005597	0.542
Fireplace	0.114386	11.134***	0.122876	8.811***	0.045837	3.121***
Garage area	0.000172	6.780***	0.000398	7.314***		
Garage area squared	–6.25E-08	–3.503***	–1.56E-07	–2.262**		
Building area	0.00032	8.391***	0.000441	11.338***	0.000286	4.478***
Building area squared	–2.33E-08	–2.900***	–5.76E-08	–7.513***	–2.82E-08	–2.562**
Lot area	9.01E-07	3.060***	1.43E-06	2.673***	1.60E-06	4.043***
Lot area squared	–3.92E-13	–1.485	–3.81E-12	–2.122**	–1.12E-12	–3.157***
Number of stories	–0.019578	–1.689*	–0.069005	–4.892***	2.02E-02	0.942
Presence of a pool	0.099166	4.186***	0.073518	3.908***		
c. *Neighborhood Characteristics*						
Airport 3 miles	0.264427	6.299***	–0.23352	–1.986**	–3.92E-01	–1.311[m]
Airport 3 miles × distance	–0.071927	–5.365***	0.079275	2.345**	0.177719	1.205[m]

Highway quarter mile	–0.194899	–0.373	–0.111048	–1.502	–2.00E-01	–2.001**
Highway quarter mile × distance	–1.412707	–0.254	0.066272	0.135	0.000205	2.931***
Air quality monitor distance	0.02556	2.042**	–0.012167	–1.402	–0.002489	–0.260^{m}
Toxic release inventory 3 miles	–0.016579	–0.241	–0.224346	–3.777***	–0.204782	–3.227***
Toxic rel. inv. 3 miles × distance	0.009512	0.512	0.044404	2.164**	0.054481	2.730***
Superfund 3 miles					0.02598	0.457^{m}
Superfund 3 miles × distance					–0.048341	–1.875*
Power plant 3 miles	–0.234856	–4.501***	–0.034007	–0.502^{m}		
Power plant 3 miles × distance			0.022193	1.002^{m}		
% Owner occupied	0.002935	4.912***	–0.003501	–4.746***	–0.003183	–2.185**
% Occupied units	–0.008693	–4.147***	–0.01032	–3.281***	–0.006517	–1.567
% Asian	0.029628	2.790***	–0.019835	–2.708***	–0.333521	–1.097
% black	–0.001705	–1.183	–0.007608	–7.050***	0.223109	0.418
% Hispanic	0.020736	1.872*	–0.028882	–2.407**	0.018075	0.049
Median Household Income	8.67E-06	7.794***	1.55E-05	10.375***	4.17E-06	4.751***
Commute time	–0.009217	–4.013***	0.003689	1.264	0.002872	0.589
Population density	–2.11E-06	–0.473	1.48E-05	3.373***	–2.82E-06	–0.284
Lake/River	–0.036878	–2.652***	0.044012	2.259**	–0.015118	–0.838
Tax rate	0.104922	2.716***	–0.038323	–3.904***	3.590921	0.591^{m}
Median year built	0.003711	3.910***	0.000698	0.817	–0.169896	–1.471^{m}
d. *Railroad variables*						
Conrail line and crossing variables						
Line impact area (LIA)	–0.067983	–4.391***	–0.063327	–1.931*	–0.089785	–2.144**
Moderate crossing impact area (CIA)	–0.087112	–3.735***	–0.090096	–2.305**	–0.031596	–0.312

TABLE 3. (CONTINUED)

Variable	Butler County		Trumbull County		Middlesex County	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
Moderate CIA × Ignore	–0.017244	–0.469	–4.72E-02	–0.731	–0.041458	–0.258
Moderate CIA × Ignore × Days since	2.23E-05	0.898	5.37E-05	1.045	2.12E-05	0.198
Severe CIA	–0.031365	–0.874	–0.182329	–1.845*		
Severe CIA × Ignore	–0.04221	–0.787	–0.327394	–2.248**		
Severe CIA × Ignore × Days since	6.27E-05	1.891**	0.000209	2.056**		
Other railroad line and crossing variables						
LIA	–0.139909	–5.265***	–0.020258	–0.690	–0.274098	–1.447
Moderate CIA	–0.095145	–3.272***	–0.160567	–2.791***	0.182837	1.594
Severe CIA	–0.039456	–0.819	0.002371	0.016	0.474631	1.525
Adjusted R^2	0.642		0.617		0.488	

F-statistic	139.95***	94.49***	35.88***
Number of observations	4725	4182	2718
Log-likelihood	–805.77***	–1359.49***	–1310.86***
e. *Unreported city* control dummy variables (Jointly significant at 95% Conf.–Wald test)	2 ($\chi^2 = 34.78$***)	4 ($\chi^2 = 26.31$***)	14 ($\chi^2 = 31.01$***)
f. *Unreported time* control variables (Jointly significant at 95% Conf.—Wald test)	12 ($\chi^2 = 407.06$***)	12 ($\chi^2 = 301.53$***)	14 ($\chi^2 = 120.01$***)
g. *Unreported school* district dummy variables (Jointly significant at 95% Conf.—Wald test)	4 ($\chi^2 = 1.12$)	12 ($\chi^2 = 54.92$***)	4 ($\chi^2 = 30.34$***)

* Significant at 90% level, 2-tailed test; ** significant at 95% level, 2-tailed test; *** significant at 99% level, 2-tailed test.

[m] Variance inflation factor on insignificant coefficient is greater than 10.

TABLE 4. HEDONIC REGRESSION EXAMINING EFFECT OF CONRAIL ACTION ON HOUSING PRICE DISTANCE GRADIENTS.

Variable	Butler County		Trumbull County		Middlesex County	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
a. *Intercept*	3.003773	1.589	9.34E+00	5.649***	343.3374	1.498
b. *Structural characteristics*						
Age house	–0.003395	–3.244***	–4.07E-04	–0.348^{m}	–1.72E-01	–1.487^{m}
Age house squared	–4.65E-06	–0.542^{m}	–4.32E-05	–3.647***	2.48E-05	3.733***
Bedrooms	0.055002	4.981***	0.049175	4.238***	0.022806	1.447
Bathrooms (OH) Full bath (MA)	0.017924	1.438	0.102252	6.400***	0.045292	2.057**
Half bath (MA)					0.075014	4.478***
Other rooms	0.023969	3.547***	0.035236	3.705***	0.005983	0.580
Fireplace	0.113483	11.041***	0.121941	9.048***	4.92E-02	3.335***
Garage area	0.000171	6.754***	3.97E-04	7.077***		
Garage area squared	–6.36E-08	–3.633***	–1.54E-07	–2.386**		
Building area	0.000318	8.386***	4.42E-04	7.084***	2.85E-04	4.435***
Building area squared	–2.26E-08	–2.825***	–5.79E-08	–3.501***	–2.83E-08	–2.559**
Lot area	9.16E-07	3.146***	1.45E-06	2.210**	1.52E-06	3.845***
Lot area squared	–4.05E-13	–1.546	–3.83E-12	–1.744*	–1.05E-12	–2.977***
Number of stories	–0.02052	–1.773*	–0.069217	–4.487***	0.018726	0.868
Presence of a pool	0.101129	4.277***	0.073974	4.442***		
c. *Neighborhood characteristics*						
Airport 3 miles	0.262504	6.231***	–0.243675	–1.712*	–0.395113	–1.314^{m}
Airport 3 miles × distance	–0.073037	–5.451***	0.082418	2.007**	0.179068	1.209^{m}

Highway quarter mile	–0.194716	–0.374	–0.126898	–1.309	–0.203131	–2.040**
Highway quarter mile × distance	–1.412739	–0.255	0.172014	0.286	0.000206	2.954***
Air quality monitor distance	0.025269	2.028**	–0.011732	–1.260	–0.002408	–0.252[m]
Toxic release inventory 3 miles	–0.005577	–0.081	–0.215741	–3.490***	–0.252978	–4.218***
Toxic rel. inv. 3 miles × distance	0.005523	0.298	0.040673	1.826*	0.064366	3.280***
Superfund 3 miles					0.022645	0.393[m]
Superfund 3 miles × distance					–0.044653	–1.727*
Power plant 3 miles	–0.242659	–4.707***	–0.02229	–0.299[m]		
Power plant 3 miles × distance			0.017441	0.702[m]		
% Owner occupied	0.002925	4.843***	–0.003508	–4.516***	–3.08E-03	–2.139***
% Occupied units	–0.008632	–4.116***	–0.00977	–3.094***	–0.006538	–1.595
% Asian	0.031016	2.919***	–0.019809	–2.510**	–0.329781	–1.090
% black	–0.001842	–1.253	–0.007692	–6.149***	2.89E-01	0.547
% Hispanic	0.019619	1.752	–2.82E-02	–2.182**	–1.28E-01	–0.348
Median household income	8.61E-06	7.700***	1.53E-05	9.349***	4.05E-06	4.739***
Commute time	–0.008954	–3.872***	3.09E-03	1.015	2.04E-03	0.421
Population density	–2.05E-06	–0.458	1.36E-05	3.028***	–4.57E-06	–0.455
Lake/River	–0.035531	–2.552**	0.044702	2.111**	–0.013579	–0.747
Tax rate	0.105338	2.699***	–0.038117	–3.165***	2.480748	0.410[m]
Median year built	0.003719	3.894***	0.000762	0.911	–0.166792	–1.445[m]

TABLE 4. (CONTINUED)

Variable	Butler County		Trumbull County		Middlesex County	
	Coefficient	*t*-stat.	Coefficient	*t*-stat.	Coefficient	*t*-stat.
d. *Railroad variables*						
Conrail line and crossing variables						
Line impact area (LIA)	–0.089171	–3.142***	–0.319479	–3.261***	–2.47E-02	–0.180[m]
LIA × Distance	0.284876	1.320[m]	1.715128	2.848***	–0.541454	–0.443[m]
Crossing impact area (CIA)	–0.039341	–1.106[m]	–0.112056	–1.230[m]	–2.35E-01	–1.701*
CIA × Distance	–1.42E-01	–1.269	0.058647	0.223[m]	2.72E-05	2.598***
CIA × Distance × Ignore	–0.014222	–0.136	–0.204594	–0.917	5.49E-07	0.070
CIA × Distance × Ignore × Distance × Days Since	4.60E-05	0.643	0.00022	1.240	–1.19E-08	–1.328
Other Railroad Line and Crossing Variables						
LIA	–2.07E-01	–2.637***	0.015228	0.209	–0.405999	–1.335[m]
LIA × Distance	0.538401	1.012	–0.160558	–0.302	–0.177961	–0.096[m]
CIA	0.010161	0.139[m]	0.065236	0.222[m]	0.843392	1.682*
CIA × Distance	–0.344353	–1.618[m]	–0.611725	–0.700[m]	–1.748785	–1.345[m]

Adjusted R^2	0.642	0.617	0.485
F-statistic	140.26	94.51	37.09
Number of observations	4725	4182	2718
Log-likelihood	–802.353	1359.18	–1310.86
e. *Unreported city* control dummy variables (Jointly significant at 95% Conf.—Wald test)	2 ($\chi^2 = 21.67$***)	4 ($\chi^2 = 8.69$**)	14 ($\chi^2 = 29.4$***)
f. *Unreported city* control dummy variables (Jointly significant at 95% Conf.—Wald test)	12 ($\chi^2 = 437.94$***)	12 ($\chi^2 = 311.73$***)	14 ($\chi^2 = 120.73$***)
g. *Unreported city* control dummy variables (Jointly significant at 95% Conf.—Wald test)	4 ($\chi^2 = 1.26$)	12 ($\chi^2 = 26.54$***)	4 ($\chi^2 = 31.18$***)

* Significant at 90% level, 2-tailed test; ** significant at 95% level, 2-tailed test; *** significant at 99% level, 2-tailed test.

[m] Variance inflation factor on insignificant coefficient is greater than 10.

significantly increase housing values in most of the samples. For Butler County, an additional bedroom increases the sale price by 5.4 percent and other rooms increase the price by 2.4 percent. Additional full bathrooms have a much stronger influence in Trumbull, increasing property values by nearly 10.3 percent, whereas bedrooms and other rooms increased values 4.8 percent and 3.3 percent respectively. In contrast, neither bedrooms nor other rooms are statistically significant for Middlesex County. An additional full bathroom increases the value by 4.4 percent and an additional half bathroom increases home sale prices by 7.5 percent.[10] The presence of a fireplace significantly increases the home sale price by 11.4 percent to 12.3 percent in the Ohio samples, and 4.6 percent in Middlesex County. This is likely serving as a proxy for other qualitative features of a home in addition to the influence of the fireplace. For example, fireplaces may be more likely to be found in homes with family rooms. Each additional story reduces the real sale price by about 6.9 percent in Trumbull, and about 1.9 percent in Butler County. The presence of a swimming pool significantly raises the sale price of the property by about 7.3 percent in Trumbull and 9.9 percent in Butler County. Turning to the square footage measures, consistent with Palmquist (1984), the square footage of the property increases housing prices but at a decreasing rate. Other things equal, the real housing price falls after 6,867 sq. ft. in Butler County, 3,559 sq. ft. in Trumbull County, and 5,071 sq. ft. in Middlesex County. In all areas, this is well beyond the mean building area. Evaluating this relationship at the mean building area value of each sample (i.e., 1,324 sq. ft. in Butler, 1,475 sq. ft. in Trumbull, and 1,863 sq. ft. in Middlesex), an increment of 100 square feet increases housing value by 3.8 percent in Butler County, 2.7 percent in Trumbull County, and 1.8 percent in Middlesex County. Additional garage area also increases values at a decreasing rate with each 100 square foot increment in garage space leading to an increase in value of 1.4 percent in Butler County and 2.9 percent in Trumbull County (again, these are evaluated at the mean values for garage area). This higher impact of garage space in Trumbull is caused by stronger marginal effects resulting from the magnitude of the coefficients in the Trumbull regression, combined with garage sizes that are on average about 46 percent larger in Trumbull. Finally, the size of the lot, which is also included in quadratic form, significantly increases the sale price of the housing unit. Again, evaluating this at the mean acreage level for the properties in the sample, this increases home values by approximately 3.2 percent per acre in the Butler County area, 5.6 percent per acre in Trumbull County, and 6.6 percent per acre in Middlesex County.

Neighborhood characteristics. The influence of neighborhood characteristics varies across locations both in terms of significance and magnitude. For example, being within three miles of the airport in Trumbull County reduces home values by 23.3 percent, but the negative effect is dissipated at 2.9 miles, since values rise 7.9 percent per mile as one moves further away for the airport. In contrast, it increases 26.4 percent within the three-mile buffer in Butler County, and then falls 7.2 percent per mile to eliminate most of the positive effect from proximity to the airport at the edge of the buffer. Proximity to an interstate highway reduces values 20 percent in Middlesex County (which is the most urban of the three areas) but the detrimental influence is completely eliminated within the quarter-mile area (i.e., values increase 27 percent per quarter mile). The real home sale price increases

2.5 percent with each additional mile from air quality monitors in Butler County, but the influence is insignificant in the other two counties. Properties in Trumbull County that are adjacent to a Toxic Release Inventory facility sell for 22.4 percent less on average, but they rise by 4.4 percent for each mile within that region. Thus, the detrimental effect is only partially offset by distance within the impact region. A similar negative impact was found in Middlesex County, but the positively sloped real housing price gradient is steeper (i.e., 5.4 percent per mile). The impact of Superfund sites is counterintuitive in Middlesex County because the real property value drops 4.8 percent per mile further from the site. It is likely that the site is capturing influences other than the perceived risks from the site. Finally, the single property that sold within three miles of a power plant in Butler County, sold for 23.5 percent less than comparable properties in the area.

Turning to the neighborhood measures drawn from 1990 census block group data, it is not surprising to find that real housing prices are higher in neighborhoods that are more affluent. Older neighborhoods, as determined by a smaller value for the *median year built* variable, have significantly lower priced housing in Butler County with an additional 10 years of age reducing the real sale price by nearly 4 percent. Surprisingly, a high percentage of occupied units significantly decreases the sale price of housing in Butler and Trumbull Counties although it should be noted that there is very little variation in this variable, and most neighborhoods have high occupancy rates. This may be capturing the influence of desirable neighborhoods that are experiencing active construction activity in Ohio. Likewise, whereas an increase in the percent of occupied homes that are owner-occupied raises housing prices in Butler County, it actually has the opposite effect in Trumbull and Middlesex Counties. Population density, which can proxy both amenities and disamenities associated with a neighborhood, on net has a positive and significant influence on housing prices in the Trumbull regression model. The racial and ethnic mix of the neighborhood exerts a statistically important influence in all three housing markets. Specifically, increases in the black population are associated with decreases in housing prices in Trumbull County; increases in Asian populations are associated with decreased prices in Trumbull County but an increase in sale prices in Butler County; and an increase in the Hispanic population is associated with decreases in home sale prices in Trumbull County but an increase in Butler County. There are a number of possible reasons for these findings. Race may be serving as a proxy for other unmeasured neighborhood characteristics, or it may be capturing racial preferences and attitudes of the majority population. It should be noted from Table 1 that concentrations of all minority groups are low in all three communities, with white populations at least 92 percent of total population in each county. Finally, consistent with the predictions of the urban location model (e.g., Bender and Hwang 1985), higher average commuting times reduce the real home price, with the coefficient significant in the Butler County regression equation. An increase in commuting time of ten minutes depresses housing prices about 9.2 percent in that city.

Being within three miles of a lake or river significantly increases home prices in Trumbull County (i.e., by 4.4 percent) whereas it significantly decreases them in Butler County (i.e., by 3.7 percent). This latter finding may be reflecting negative consequences associated with proximity to rivers, such as flooding. Unfortunately, residence in floodplains is not controlled in the regression models. Turning to fiscal measures, a high property tax burden depresses housing prices in Trumbull County, but it increases them in Butler County. Because the value of public services is only partially controlled in the regressions, tax rates may be capturing both the tax burden and also the benefits of uncontrolled services. Several coefficients were included in the regression models but are not reported in Tables 3 and 4 to conserve space. Specifically, dummy variables for the school district, where the properties are located, are found to have a jointly significant impact on the real price of properties selling in Trumbull and Middlesex Counties. Likewise, the dummy variables for the jurisdiction of the property sold are highly significant in all three counties. These variables partially control for the provision of local public services in the community.

Time and seasonal dummy variables. The time and seasonal dummy variables are jointly significant in all equations. The coefficients on seasonal dummy variables reveal that housing prices in Butler County are significantly higher in the fall than in the winter, which is the omitted category, whereas they are significantly higher in the summer in Middlesex. In addition, real housing prices have risen over the 1988–1997 period, with the real appreciation rate approximately 29.2 percent in Butler County and 26.9 percent in Trumbull. The housing market in Middlesex is substantially stronger, with real price appreciation of 175.4 percent over the 11-year period. This is in spite of a relatively deep recession in New England during the late 1980s.

Railroad related variables: Specification 1. The first specification (shown in Table 3) assumes that there are two distinct impact areas for rail crossings. The severe impact area is the area defined within 1000 feet of the crossing, whereas the moderate impact area is defined as the zone between 1001 and 2320 feet of the crossing.

Proximity to rail lines. Turning to the findings on railroad variables in the first specification, controls for proximity to both Conrail and other rail lines consistently reveal that properties within 1,000 feet of a rail line experience significantly lower home sale prices. The reductions in sale prices for properties along Conrail lines are significant in all areas, with real prices falling between 6.3 percent and 9 percent as compared to properties outside the Conrail line impact area. In the only county showing a significant impact along other lines, Butler County, the impact was more substantial at −14 percent. These findings are slightly larger than those found elsewhere. For example, Simons and El Jaouhari (2004) found negative impacts in the 2 percent to 4 percent range, whereas Strand and Vagnes (2001) found impacts in the −10 percent range within 100 meters of the tracks.

Proximity to crossings. Turning to the impact areas surrounding the crossings, some consistent patterns do emerge although there are some exceptions as well. Specifically, an examination of the baseline effects in the moderate impact area of the Conrail crossings reveal significantly lower home prices in the impact areas for properties selling in the Ohio counties. Indeed, they are 8.7 percent lower in the Butler moderate impact area (as compared to outside the area) and 9 percent lower in the Trumbull County moderate area. For other lines, there are somewhat higher negative baseline effects in the Ohio counties (–9.5 percent in Butler and –16 percent in Trumbull). The severe impact areas for Conrail crossings are negative and significant for Trumbull County, and as expected, the negative impact is greater in the severe impact area (i.e., –18.2 percent as compared to –9 percent in the moderate zone). Finally, none of the coefficients in the severe impact area (other) category are statistically significant. Note that activity levels at these crossings are not controlled, which can influence the findings. Although information was collected from the Federal Railroad Administration on activity levels at the crossings, these data were not consistently defined over time. Furthermore, of the three areas considered, only Middlesex County had activity levels that exceeded fifty trains per twenty-four-hour period, which is the threshold activity level identified by Sörensen and Hammar (1983) as they measured annoyance levels among residents.

Effects of Conrail action. Examining the effect of the Conrail action, there is no evidence of a permanent negative impact associated with the Conrail policy. None of the interaction terms between the *Moderate CIA* variables and the *Ignore* variable were statistically significant. Of the two counties with properties selling in the *Severe CIA*, only Trumbull County showed a significant negative effect from the action (i.e., a reduction in sale price of 32.7 percent). However, the impact was significantly diminished over time. That is, the coefficient on the *Days since* interaction term was positive and significant, suggesting that property values rose 7.6 percent for each year that passes after the Conrail action. This suggests the negative effect of the Conrail action would be eliminated in approximately 4.3 years. Note that the log-linear increase in the sale price resulting from the influence of the *Days since* variable would not be expected to continue indefinitely because it is unlikely that the Conrail action would actually increase property values. However, these estimates do suggest that within the relevant range of the data, more than a third of the negative impact of the Conrail decision on local property values was eliminated. That is, at the mean value of *Days since* (548 days), property values would have rebounded by approximately 11.5 percent, and hence, the negative impact of the Conrail action is mitigated over time.

Railroad related variables: Specification 2. The second specification (shown in Table 4) estimates continuous price-distance gradients, which measure the rate at which housing prices change with the distance of the property from the rail line or rail crossing. The findings are similar in many respects to those found in the previous specification, but there are some important differences as well.

Proximity to rail lines. The coefficient estimates on the LIA dummy variables consistently reveal negative and significant property value impacts. For Conrail lines, the price reductions range from about 8.9 percent in Butler County to 31.9 percent in Trumbull County. For other lines, real housing price reductions of 20.7 percent were seen in Butler County. While these values are larger in magnitude than those found in the first specification, there is an important difference in the interpretation. For the first specification, no gradient was estimated. Hence, the coefficient on the LIA variable represented the average impact over the entire impact area. In this specification, the LIA dummy variable is included, and it is also interacted with the distance of the property from the line. Thus, the coefficient on LIA is now interpreted as the impact at the closest point to the rail line, rather than the average impact over the entire impact area. The interaction between LIA and *Distance* measures the marginal effect of distance from the rail line, within the LIA. Three of the six gradients are positive, although only one is statistically significant. Specifically, the coefficient on the *LIA * Distance* interaction term in the Trumbull County regression is 1.715, indicating that prices rise 32.5 percent in the 1,000 foot LIA. This suggests that the 32 percent reduction at the edge of the track is eliminated within 1,000 feet of the railroad line. Given the high VIF scores on some of the insignificant coefficients for the other areas, it is possible multicollinearity is partially responsible for the low levels of significance in the Butler and Middlesex regressions.

Proximity to rail crossings. Turning to the analysis of rail crossing measures, there are some interesting results. For other rail lines, the coefficient on the CIA in Middlesex County is positive and significant. That is, real home prices are 84.3 percent higher for properties located at intersection, but they then fall (albeit with a *t*-score of −1.345)[11] at a rate of 43.7 percent per quarter mile from the crossing. It may be that this is capturing in part the possibility that some of these crossings are also commuter rail stations. It should be noted that the non-Conrail Middlesex crossings are the only ones for which train activity levels exceeded fifty trains per day (i.e., there were sixty-two trains per day in one location). Finally, I point out that in Butler County, the coefficient on the interaction term *CIA * Distance* was negative and approaching significance at the 90 percent level of confidence. It is unclear as to the reason for a negatively sloped gradient in this county because there is no commuter rail in the county. Again, multicollinearity may be contributing to the insignificance of some of the rail crossing gradients in this specification.

Examining the coefficients on the Conrail *CIA* variables, the only coefficients that are statistically significant are found in Middlesex County although the findings in Trumbull County may be insignificant because of multicollinearity. Here, the coefficient on *CIA* was negative (–23.4 percent at the track edge). Furthermore, the gradient had only a very slight positive slope changing less than 0.1 percent over the quarter-mile range of the impact area. Both of these effects can be viewed as having been in existence before the Conrail action to ignore the local whistle ban. To consider the impact of the Conrail action, one must evaluate the interaction terms with the *Ignore* variable. All of the coefficients on *CIA * Distance * Ignore* were statistically insignificant, as were all of the coefficients on the *CIA * Distance * Ignore * Days since* interaction term. These findings suggest that the decision by Conrail to ignore the whistle bans did not significantly change the shape of the housing price gradients in the neighborhoods around the crossings, either immediately after the Conrail action or in the months that followed their decision.

Conclusions and Policy Implications

The findings consistently show that proximity to rail lines has a negative and statistically important influence on residential property values. In addition, there is evidence that proximity to rail crossings can also reduce the real sale price of homes. In fact, all of these impacts existed before the point at which Conrail began ignoring the train whistle bans in these three areas. However, the overall weight of data reveals little evidence that the decision by Conrail to begin ignoring whistle bans had any permanent and appreciable influence on the housing values in these communities. For two of the three study areas, there was no statistically significant influence of the Conrail action. Furthermore, in the only area where a negative effect was identified (i.e., Trumbull County), one model suggested the effects were minor and temporary (i.e., property prices rebounded within about 4 years).

This is not necessarily surprising. Individuals buying properties within the potential audible range of a rail crossing likely consider at least the possibility that train whistles will be blown at the crossing in the future. Thus, when Conrail began ignoring the ban, it may have only confirmed their initial suppositions. Furthermore, it is likely that the Conrail action generated dynamic changes in the composition of residents that served to mitigate the initial impact of the action. Residents most sensitive to train whistle noise would be expected to eventually move away from the impacted area, and they would be replaced with those less bothered by train whistles. This is because the residents most tolerant of train noise would have the highest willingness to pay for the property when it is on the market. This transition from more sensitive to less sensitive residents would reduce and possibly eliminate any long-run impacts from the Conrail decision that could explain the insignificant coefficients in two of the three study areas.

This study has important implications for policy makers. In a cost-benefit analysis of the impacts of lifting of whistle bans, one component of the costs of such a policy would be the reduction in property values for properties in the vicinity of rail crossings. These costs would then be weighed against the benefits of the policy change (i.e., reduced societal costs from accidents). These findings suggest that for communities with low to moderate train activity (i.e., less than seventy-five trains per day), the costs in terms of property value reductions appear in most cases to either be negligible, or minor in magnitude and temporary in duration. Thus, it is likely that removal of train whistle bans results in positive net-benefits to society. These findings, while enlightening, are just first steps in understanding how train whistles influence local property markets. More complete data is needed to achieve a thorough understanding of the factors leading to residential property price impacts of train whistles. This includes continuously defined data on train activity levels. Next steps should also investigate the relationship between distance, terrain, and the presence of other factors such as tall buildings that can serve as barriers to noise. Moreover, the analysis could be extended to study areas in other geographic regions. For example, all of the study areas in this study were in the Northeast or North Central regions. In more moderate climates, residents likely spend more time outdoors year round. This may influence their sensitivity to train whistle noise. Note also that this study has focused on property impacts from train whistles. There are other whistle impacts that could also be investigated, including the effect on residential mobility. That is, does a change in policy regarding train noise motivate some residents to move out of the audible range of trains?

Although this study suggests that this dynamic process may be at work, more direct measures of mobility are needed before strong conclusions can be drawn. Finally, this study focused exclusively on residential property. Train whistle noise may also influence the value of commercial property, and an empirical investigation of commercial impacts is needed to understand more fully the impacts of a policy change regarding train whistles.

NOTES

1. There are a number of reasons why stated preferences and revealed preferences derived from hedonic approaches may differ. One of the assumptions of the hedonic model is that homebuyers know the true level of the local amenity bundle. This is not always the case, however. For example, Bernknopf, Brookshire, and Thayer (1990) document that earthquake and volcano hazard risk notices influence local property markets. Homebuyers who are unaware of such risks pay more for housing than those who are notified of their presence. Likewise, Clark and Allison (1999) show that the visual cues and media coverage about stored nuclear waste influence housing price gradients for nuclear power plants.
2. Rosen (1974) shows that this implicit price does not represent an individual's willingness to pay for the attribute. The implicit price can be used, however, to derive the demand for an attribute in a second stage estimation process. Brown and Rosen (1982), Diamond and Smith (1985), Epple (1987), Bartik (1987), and others, however, have noted the existence of identification problems that make estimation of these demand functions difficult. The current study need only focus on the single stage model.
3. The ArcView 3.1 GIS software with the Streetmap was used to geocode each property. Only properties with complete address information were geocoded, and the author required an average score of 80 out of 100 on the geocoding index reported by ArcView to keep the observation.
4. The issue of functional form has been investigated extensively in the hedonic literature. Although some authors (Rasmussen and Zuehlke 1990) advocate flexible functional forms, others have voiced concerns about the accuracy of implicit prices from such forms (Cassel and Mendelsohn 1985). Cropper, Deck, and McConnell (1988) argue that the semilog model is preferred when the possibility of a misspecification exists. While I have been careful in the choice of specification, such a possibility exists with spatially defined data.
5. Older homes are expected to include more dated technology (e.g., some may not include central air conditioning), and hence, may be less desirable. However, older homes may also include features such as hardwood floors, crown molding, and so on that are less likely to be found in newer homes. In addition, Palmquist (1984) has argued that building area should be included nonlinearly because construction costs increase nonlinearly with the size of the house. Hence, the author includes area measures in linear and quadratic form. Overall, linear terms for the age and area variables are expected to have a positive influence on sale prices, and the quadratic terms are expected to negatively impact prices.
6. Note that only Middlesex County had a site on the National Priorities (a.k.a. Superfund) list that matched to a property that was within three miles. There were Superfund sites in the other counties, but all of the properties fell outside the three-mile impact area.
7. The Toxic Release Inventory is a publicly available database of firms that emit toxic chemicals into the environment. It was created in response to the 1984 Bhopal accident in which a Union Carbide

plant accidentally released methyl isocyanate gas. Some estimates indicate that more than half million people were exposed to the gas, and more than 20,000 eventually died from their exposures. Given that some of these properties sold during the late 1980s and early 1990s, it is possible that knowledge of TRI sites could affect their bid prices.

8. The definition of impact areas for environmental goods is admittedly arbitrary. It should be noted that the dummy variable definitions and/or the distance variables interacted with those variables are all significant in at least one of the regression equations reported in this article.
9. Nearly identical specifications are included in all three regressions so that the findings across locations can be compared without fear of a specification bias. As long as a variable is found to be significant in at least one regression, the variable is retained in all three regressions. Because multicollinearity can lead to insignificant coefficients, Variance Inflation Factor (VIF) scores were computed for all insignificant coefficients. When the VIF $>$ 10, this is denoted in Tables 3 and 4.
10. It may initially seem odd that a half bathroom is valued more highly than an additional full bathroom. However, note that all homes have at least one full bathroom, and thus an incremental bathroom is the second bathroom. Indeed, 50.2 percent of the homes in Middlesex County had one and 42.9 percent had two bathrooms. In contrast, about half of the homes do not have a half bathroom.
11. Note again that the coefficient on *LIA * Distance* has a VIF score that exceeds 10.

REFERENCES

Bartik, T.J. 1987. The estimation of demand parameters in hedonic price models. *Journal of Political Economics* 95: 81–88.

Bender, B., and H.-S. Hwang. 1985. Hedonic price indices and secondary employment centers. *Journal of Urban Economics* 17: 90–107.

Bernknopf, R.L., D.S. Brookshire, and M.A. Thayer. 1990. Earthquake and volcano hazard notices: An economic evaluation of changes in risk perceptions. *Journal of Environmental Economics and Management* 18: 35–49.

Björkman, M. 1991. Community noise annoyance: Importance of noise levels and number of noise events. *Journal of Sound and Vibration* 151(3): 497–503.

Brown, J.N., and H.S. Rosen. 1982. On the estimation of structural hedonic price models. *Econometrica* 50: 765–768.

Cassel, E., and R. Mendelsohn. 1985. The choice of functional forms for hedonic price equations: Comment. *Journal of Urban Economics* 18: 135–142.

Clark, D.E., and T. Allison. 1999. Spent nuclear fuel and residential property values: The influence of proximity, visual cues and public information. *Papers in Regional Science* 78: 403–421.

Cropper, M.L., L.B. Deck, and K.E. McConnell. 1988. On the choice of functional form for hedonic price functions. *Review of Economics and Statistics* 70(4): 668–675.

Diamond, D.B., and B.A. Smith. 1985. Simultaneity in the market for housing characteristics. *Journal of Urban Economics* 17: 280–292.

El Jaouhari, A., and R.A. Simons. 2002. The effects of rapid transit lines and stations on residential property values in Cuyahoga County, Ohio. Unpublished manuscript.

Epple, D. 1987. Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economics* 95: 59–80.

Federal Railroad Administration (FRA). 1992. *Florida's train whistle ban*, 2nd ed. Washington, DC: U.S. Department of Transportation.

———. 1995. *Nationwide study of train whistle bans*. Washington, DC: U.S. Department of Transportation, Office of Safety.

Freeman, A.M., III. 1979. *The benefits of environmental improvement: Theory and practice*. Baltimore, MD: Johns Hopkins University Press.

Galster, G.C. 1986. Nuclear power plants and residential property values: A comment on short-run vs. long-run considerations. *Journal of Regional Science* 26: 803–805.

Haurin, D.R., and D. Brasington. 1996. School quality and real house prices: Inter- and intrametropolitan effects. *Journal of Housing Economics* 5(4): 341–368.

Kiel, K.A., and K.T. McClain. 1995. House prices during siting decision stages: The case of an incinerator from rumor through operation. *Journal of Environmental Economics and Management* 28: 241–255.

Lancaster, K.J. 1966. A new approach to consumer theory. *Journal of Political Economics* 74: 132–157.

McDougall, G.S. 1976. Hedonic prices and the demand for local public goods. *Public Finance* 31: 265–279.

Metz, W. 1994. Potential negative impacts of nuclear activities on local economies: Rethinking the issues. *Risk Analysis* 14: 763–770.

Multer, J., and A. Rapoza. 1998. Field evaluation of a wayside horn at a highway-railroad grade crossing. Report DOT-VNTSC-FRA-97-1, Federal Railroad Administration, U.S. Department of Transportation.

Osada, Y. 1991. Comparison of community reactions to traffic noise. *Journal of Sound and Vibration* 151(3): 479–486.

Palmquist, R.B. 1984. Estimating the demand for the characteristics of housing. *Review of Economics and Statistics* 66(3): 394–404.

Rasmussen, D.W., and T.W. Zuehlke. 1990. On the choice of functional form for hedonic price functions. *Applied Economics* 22: 431–438.

Rosen, S. 1974. Hedonic prices and the implicit markets: Product differentiation in pure competition. *Journal of Political Economics* 82: 132–157.

Rylander, R., M. Björkman, U. Åhrlin, S. Sörensen, and K. Berglund. 1980. Aircraft noise annoyance contours: Importance of overflight frequency and noise level. *Journal of Sound and Vibration* 20: 527–530.

Sörensen, S., and N. Hammar. 1983. Annoyance reactions due to railway noise. *Journal of Sound and Vibration* 87(2): 315–319.

Simons, R.A., and El Jaouhari, A. 2004. The effect of freight railroad tracks and train activity on residential property values in Cuyahoga County, Ohio. *The Appraisal Journal* 72(3, Summer): 223–233.

Strand, J., and M. Vagnes. 2001. The relationship between property values and railroad proximity: A study based on hedonic prices and real estate brokers' appraisals. *Transportation* 28: 137–156.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48: 817–838.

Attachment D
Exhibit 4005-000030-CWF
Columbia Waterfront LLC