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Valuation of Specific Crime Rates: Final Report

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INTRODUCTION

Evaluating the explicit costs of crime to society is a difficult task, as seen in the few number of researchers that have attempted to solve this problem. However two main approaches have emerged in these endeavors. The most tried technique has used hedonic models, dating back to Richard Thaler's "A Note on the Value of Crime Control: Evidence from the Property Market" in the *Journal of Urban Economics* (1978). Using this type of model, researchers have strived to isolate the value individuals place on specific amenities or disamenities, such as weather, air pollution and crime rates, as seen in the wages they require and the prices they pay for housing.

The other technique evaluates these costs by combining the actual out-of-pocket expenses associated with crime with the imputed costs from the pain, suffering and fear endured by crime victims. Mark Cohen computed these values for specific crimes for the first time in "Pain, Suffering, and Jury Awards: A Study of the Cost of Crime to Victims" in *Law and Society Review* (1988). Both methods have their limitations. The hedonic approach has allowed researchers to derive a value for an index measure of crime, but not for specific crimes. Cohen's technique allowed him to examine estimates for individual crimes, but not without sacrificing the market-based analysis of the hedonic models which estimates the costs of crime based on individuals' voluntary decisions.

I combine these two methods to obtain a market-based estimate for specific crimes. Incorporating a data set I used for my article in *Economic Inquiry* (1998), I obtain detailed nationwide information on specific crimes committed at the county level.

Expanding other researchers' use of the US Census Bureau's *Population and Housing Surveys* [Blomquist et al. (1988), Clark and Nieves (1994), Cragg and Kahn (1997), Kahn (1995) and Hoehn et al. (1987) just to name a few] with hedonic models, I use multiple decades of information obtained from counties across the United States to create a panel data set. With this data, I isolate the effects that individual crimes have on housing prices and wage rates, as seen by individuals' and households' preferences changing over time. I then place a dollar value on the benefit of specific crime reduction, as perceived by their willingness to pay.

I follow this introductory section of the paper with a literature review, an explanation of methodology, a data preparation section, an analysis of the data and a concluding section.

CHAPTER I

LITERATURE REVIEW

Micro-level Hedonic Studies

The hedonic models have come in many forms. Most can be separated into either micro or macro approaches. The micro-level studies primarily concentrate on explaining variation in housing prices in relatively small sample areas [see Dubin and Sung (1990) and Buck et al. (1993)]. Data from Rochester, NY was the choice for the model used by Thaler (1978). He incorporated the number of property crimes per population in a regression of land uses and attributes on the dependent variable of the value of land. With estimates for the average cost of such crimes, he alluded to computing "the optimal level of criminal justice expenditures *a la* Becker" (p.144). Gary Becker (1968) had set forth the importance of studying crime econometrically in a cost-benefit analysis.

Other researchers were looking towards my same goal over two decades ago. Rizzo (1979) studied the effect of crime on property values within the Chicago metropolitan area using a hedonic model. Hellman and Naroff (1979) examined the impact of crime on urban housing prices using data from the city of Boston. Both used an index measure of crime to find that increased levels of crime negatively affect the prices individuals are willing to pay for housing.

Many of these hedonic models were spawned from the early work of Richard Muth (1969). In his predominantly theoretical work he examined many of the intricacies involved in pricing housing. He applied basic economic models of marginal utility, income and transportation costs in modeling an individual's decision to locate within a city. The central business district (CBD) was a mainstay of his arguments. It was the location of many amenities, such as the theater or arts center, as well as the center of employment for much of the population. Living close to the CBD cut down on travel time and transportation costs, but also raised the price of housing given the higher demand for proximity to the CBD. Individuals chose the location, quantity and quality of housing they consumed as a part of a package of utility combining other goods, transportation costs, income and preferences.

By examining individuals' decisions, he aggregated his model to a theory of location and pricing of housing to explain many of the phenomena found in a city's development. He showed that different housing types, such as apartment buildings versus single-family dwellings, would mostly be located at different distances from the CBD due to varying rental gradients for the properties. Certain areas of a city were prone to slum conditions due to the age and style of the housing present and the difficulty of redeveloping these areas due to small lot sizes, varying depreciation rates and zoning restrictions. These are just some stylized facts he was able to explain, but since this book, much work has been done to expand these ideas.

The work by Rizzo (1979) typifies the predominant type of crime study in this area. He studied seventy-one communities within Chicago in 1970 to which he could attribute crime rates, in the form of three-year averages of a crime index. From Census data, he acquired the aggregate property values for each area based upon rents paid and upon owner estimates. He regressed the log of these values against the crime variable and general "environmental" variables such as the median number of rooms per home, proportion of whites in population, amount of public housing, distance to central business district, etc.... He found a negative impact from the crime variable. He used this coefficient to estimate the yearly cost to Chicago of doubling crime. This research is very typical of the time of using a single city and aggregate property values to study crime.

Macro-level Hedonic Studies

Incorporation of Amenities

In the early stages, some researchers realized that amenities or the lack thereof are a major determinant of housing location. The presence of a coastline or high humidity may add or detract from a city's general attractiveness compared to other cities and will be accounted for in a market system in some fashion. At the same time, location within a specific area of a city should also yield compensating differentials. These may arise due to the presence of better schools or more crime than in other parts of the city. This study of specific amenities has transformed into an entirely new avenue of research.

Researchers undertook a variety of techniques to expand this type of study. Timothy Bartik (1987) found that multi-market data is needed for identification in hedonic estimation because single-market data can not solve the endogeneity problem that may exist in hedonic estimation. Sherwin Rosen (1979) was among the first to use data on such a macro level. Specifically he used the US Census' *Current Population Surveys* to make quality-of-life comparisons between different areas or cities. These surveys allowed him to use personal characteristics of individuals in his estimates of amenities. He did use a total measure of crime in his regressions, but the results were not as robust as those he found for pollution or for climate measures, i.e., the resulting coefficients for crime were often insignificant or of the wrong sign. Also he used the survey data to form wage hedonic equations to determine his implicit amenity prices, based on the earlier theoretical work of Rosen (1974). In that piece, he stressed the market format that exists between buyers and sellers in maximizing their utility and profit.

Other researchers also looked to find these differentials being bid into wage rates, but Maureen Cropper (1981) was one of several authors that discovered that the coefficients found using only wage-based hedonic analyses were not unbiased estimates of the marginal value of the amenities. She realized that land prices would be affected by changes in population, which could be driven by the amenities. Bartik and Smith (1987) advocated using only hedonic property value models, and not including wage equations, because they believed the assumption of national labor and housing markets was inaccurate. However many other researchers to be outlined below advocate the use of both wages and property values in hedonic models to be able to derive an implicit price of an amenity.

Jennifer Roback (1982) constructed a model that used both wages and rents in evaluating amenities. Her argument was that, as individuals desire amenities, in whatever form, they would be willing to accept lower wages or higher prices for housing. Part of the marginal value of the amenities will be captured in housing costs as individuals often work far from their residence where many of the amenities will be experienced, so wages should not capture all the value of the amenities. Again this author also used an index measure of crime rather than specific crime rates.

Work of Hoehn, Berger and Blomquist

Hoehn, Berger and Blomquist (1987) set out to develop a model to yield an unbiased estimator of amenity values that could be used for policy analysis using both wages and housing prices. Using the theories of these earlier authors, they proposed that housing prices are most likely determined by individuals weighing the attributes of the housing itself, their wages and local amenities, such as the weather or access to the arts. Locating themselves in a particular city within a specific neighborhood in a certain occupation, individuals make conscious decisions to trade off the good with the bad. With a specific income, an individual can afford only so much quantity and quality of housing. It may require substitution to poorer standards, due to budget constraints, in exchange for proximity to amenities such as a beach or good schools. Or the individual can change his occupation to make a completely new decision.

These authors began their model with a utility function $U = U(x, s, L)$ where x is a composite consumption good, s is an index of amenities and L is residential land. They set up a system of equations describing: 1) maximized utility depending upon the local wage w, land prices at the specified distance r from the CBD and the amenities s present; 2) an intraurban utility equilibrium based upon the local wage, the opportunity cost of residential land at the rural-urban fringe, the rural boundary of the residential area and the amenities present; 3) population of the urban area depending upon the rural boundary of the residential zone and population density; and 4) unit production costs equaling the unit product price within the CBD in equilibrium.

This system of equations could be used to find the comparative static results of changes in amenities on wages, land rents, the rural boundary and population size. The partial derivation yielded $f_r = k_r dq_r/ds - dw/ds$, an equation for the marginal value of amenities at any given point *r* within the area, where k_r is the quantity of housing purchased and q_r is the product price of the local good (including transportation costs) at that distance. The first term is the effect on housing expenditures from the change in amenities, and the second term is the differential arising in total earnings. They hypothesized that higher housing prices and/or lower wages would be accepted for greater levels of an amenity. Thus the implicit price of amenities could be computed from coefficients from housing and wage hedonic equations without the actual use of land rents.

Hoehn et al. used the 1/1000 Public Use A Microdata Sample of the 1980 *Census of Population and Housing* to obtain detailed information on individuals and on households across the country. They utilized other information they acquired on proxies for amenities in the individuals' area of habitation. These included weather variables from the National Climatic Data Center, environmental concerns from the Environmental Protection Agency and urban variables they constructed. With this information, they ran regressions for separate wage and housing models using a limited Box-Cox format. Each model used independent variables gleaned from the census information, accompanied with the variables for amenities or disamenities they had compiled. Their housing hedonic equation used the dependent variable of monthly housing expenditures for 1980, and the wage hedonic equation used a computed hourly wage rate in 1980 for the working individuals in the household.

Using the coefficients derived from each of the models for a particular amenity, the researchers combined them to obtain a hedonic dollar value that individuals attribute to specific amenities or disamenities. For example, if individuals view humidity as a disamenity, we would expect them to demand higher wages for a given occupation or lower prices for a given housing unit, as compared to these things within a location with less or no humidity. The authors found both of these effects present with humidity, with a mean level of 68 percent at the households sampled. With a 10 percent increase in humidity, the researchers found that households had lost $296.52 each in yearly benefits in 1980 dollars.

The amenity variables used in the regressions of Hoehn et al. are commonly accepted for these hedonic estimations. Bartik and Smith (1987) provided a summary of the policy studies of urban amenities performed with hedonic methods up to that point in time. They concentrated on the micro or intraurban effects of amenities, but they cite the predominant use of variables for school quality, crime, air quality and access to work or commerce, including transportation costs, among different studies. They also explored research using the expenditures by government bodies on education, crime prevention and water and air quality to improve these amenity values and thus urban housing location.

Hoehn et al. computed the values of their (dis) amenity variables for an average household in 1980 dollars per year using over 34,000 households and 46,000 workers in their computations. All amenity values were significant and had the expected sign except for visibility, which was calculated as a disamenity although it was insignificant. The amenities included a coastline, residence in a central city, more sunshine, precipitation and a greater teacher-pupil ratio; the others were found to be disamenities, including crime.

The researchers showed the importance of using both wage and housing differentials as many amenities or disamenities had opposite signs from those expected for the partial implicit prices in the wage and housing regressions. For example the partial price from the housing market indicated that residing within the central city was a disamenity, but the differential from the labor market was positive enough to make this variable an amenity. They used such examples to show why using the coefficients from a single hedonic equation, whether it be from wages or from housing, will seriously bias the estimate of the amenity's value.

Work of Clark and Nieves

Clark and Nieves (1994) attempted this same type of analysis to examine the individual impact of different noxious facilities on property values, also using Census data from 1980. Whereas Hoehn et al. (1987) did account for such an effect by using Superfund sites as a disamenity, Clark and Nieves used eight different types of facilities as variables. Beginning from the same basic model as Hoehn et al., they controlled for violent crime and most of the same climate and environmental variables in both wage and housing price equations to calculate implicit amenity prices. They also included several additional variables to account for varying price, disequilibrium, location and fiscal factors, to be discussed more later in the text, which they hypothesized would also affect the wage-housing price trade-off. I include many of these same extra variables in my model to further limit omitted variable bias. Clark and Nieves found that six of the eight noxious facilities were classified as disamenities when combining the implicit amenity prices from both the housing value and wage equations, although only two were significant.

Assumptions of Hedonic Models

As with any model, these researchers must make sacrifices in the construction of their analysis when using hedonic models. They are studying the decisions of individuals spread out across the United States. They know the general location of the individual's home, perhaps as far as a certain part of a county. They can not specifically measure amenities for each particular home from the census data or the preferences of each individual for the amenities because the census data ensures confidentiality of the participating individuals. The problem of omitted variable bias is sometimes cited as a weakness of the hedonic approach. We can not know the underlying structural equation; however, what is important is the reasonableness with which we approach this mark. Measurement of certain amenity variables such as precipitation or the amount of total suspended particulate (TSP) should not be a problem because most people in the area will experience generally the same weather or pollution with this type of data.

Other variables, such as the teacher-pupil ratio, which proxies for educational availability, are slightly more difficult to interpret because this information is generally available at a more aggregate level, such as the county. However we do not know the types or quality of schooling available to every particular household. I would postulate this to be an issue for many studies because even an exact location for the house will not yield this information as parents can transport their children to different schools throughout the area. Again the wages and housing prices should, in part, reflect the general opportunity to access better schools in one particular city over another, so I believe the authors still accomplish their goals. Thus I will follow the basic model outline set up by Roback (1982) and Hoehn et al. (1987).

With this type of study, researchers are limited in the amount of detail they can ascertain. Census data does not identify any geographic area with less than 100,000 population to ensure confidentiality. In sparsely populated areas, a "geographic area" defined by the Census may contain thousands of square miles and many different counties, so the authors concentrate on the true SMSAs that can be identified. Secondly some information, such as the detailed climate information, is most readily available at the SMSA level and not for small counties or cities. Many amenity prices that the researchers find, such as for crime, may be less than their true value for comparing all locations across the United States. We assume that there is less variation between SMSAs for such variables than between a city such as Chicago and a small town in Montana, where the latter may not be identified or measured here.

Berger et al. (1987) used the amenity prices they derived to rank the geographic areas identifiable through the Census information, those with over 100,000 population, based on a quality-of-life index. Blomquist et al. (1988) used the same amenity prices to rank the individual counties within these metropolitan areas on a quality-of-life basis, allowing for even more variation within locations where possible. As mentioned before, Hoehn et al. (1987), and others, were not studying the impacts of specific crimes on housing costs. Those who have attempted this task did so theoretically, like Hakim and Weinblatt (1984), who hypothesized how different property crimes, without quoting any empirical data, will affect land values due to different net returns and transportation costs for the four different property crimes studied.

All of these authors utilized the experience of a history of researchers using these hedonic techniques to estimate amenity values. This approach is accepted within the academic community, both in theory and in practice. Smith and Huang (1995) performed a meta-analysis of many earlier studies of the effect of the disamenity of air pollution on property values through hedonic estimation. Cragg and Kahn (1997) specifically studied the demand for climate as an amenity with this technique, using Census data from 1990. Craig et al. (1998) used a county-level hedonic model to historically test the effect of water and rail access on farm values between 1850 and 1860. As former chief statistician for the Bureau of Economic Analysis (BEA), Frank de Leeuw (1993) helped to construct a price index for new multifamily housing using hedonic estimation. This index is used to convert expenditures to constant dollars, just like the hedonic index that has been used by the US Census Bureau for several years for new one-family houses.

Estimation of Individual Crime Costs

The other major approach to estimating the costs of crime is to use the technique of Cohen (1988). In this piece, he used both direct and indirect methods to achieve crime-specific cost estimates. He transformed the actual risk of death or injury faced by crime victims into dollar figures using estimates of the value of life and court awards in personal injury cases. In this way, he could attribute a cost per crime according to the risk involved with each one. His cost estimates, when aggregated, were very similar to those obtained by authors using the hedonic approach, such as that of Thaler (1978) and other authors, which he showed in Cohen (1990).

CHAPTER II

METHODOLOGY

Combination of Approaches

We know of general areas in our cities of residence from word of mouth or press coverage that are prone to criminal activity. We expect to see compensating differentials in housing prices from safe to dangerous areas. We must also remember that crimes are not just pertinent to the home. Individuals are exposed to crime at or in transit to places of employment, schools, or other areas of a city that they may visit for shopping, for entertainment or for a host of other reasons. Aggregating this analysis to compare separate counties or cities should not detract from the validity of the effects of crime being found on housing prices in models such as that of Hoehn et al. (1987).

I utilize the county-level approach of Hoehn et al. to more closely study the impact of different types of crime on an individual's choice of location, specifically in housing. These authors viewed the violent crime rate, as measured by the number of crimes committed per 100,000 people, as a disamenity in a collective measure. From their calculations, a nationwide policy that reduced violent crimes by ten percent would have been worth nearly $5.4 billion in 1980 in estimated aggregate benefits as measured by a household's willingness to pay in terms of wages and housing prices. I believe that individuals consider the level and location of crime more seriously than this estimate in their choice of location, especially with the publicity afforded it. Using the same type of hedonic model as that of Hoehn et al., I compute a dollar value that individuals will bear, in their wages and in their housing costs, to reduce the rates of specific crimes.

Researchers have not studied specific crimes in part due to the problem of collinearity; that is, the crimes of assaults and of burglaries may increase together. I compensate for this problem by adding more information from the 1990 *Census of Population and Housing* to the 1980 data that Hoehn et al. and Clark and Nieves (1994) used. In this way, I can use a nationwide panel data set that will allow me to see how housing and occupation choices within particular locations have changed over the decade considering all amenities or disamenities, including specific crime rates. Kahn (1995) used Census data from both 1980 and 1990 to attempt to rank the quality of life in different cities in the United States. However he used a revealed preference approach, rather than a hedonic measure, and did not specifically study crime.

Many of the amenities or disamenities I include in my hedonic study will not change significantly over the period between 1980 and 1990 for individual areas of residence, such as the variables involving weather and the environment. Incorporating the same independent variables for the wage and housing hedonic equations for the more recent data will highlight the importance of amenities that are changing over time, such as the crime rates. From my research with concealed gun laws mentioned in the Introduction, I know that the rates of specific crimes committed do not necessarily increase or decrease at the same rate or for the same reasons, especially across different regions and time periods. I use these varying rates to determine the relative value that individuals place on reducing certain crimes. This technique also allows me to verify that a misspecification error is not driving the results of previous research, as claimed to be another potential pitfall of using hedonic analysis.

I do more than simply add 1990 data to the model of Hoehn et al. to derive my model. First I use Sample B Census data rather than the Sample A data of Hoehn et al. The Sample B data includes information from more urban areas because it includes urban areas that cross state lines while the Sample A data does not. Clark and Nieves utilized this same data set. I include some of the fiscal factors of Clark and Nieves that Hoehn et al. did not. Buck et al. (1993) explored the dichotomy of some governmental spending increasing property values, but at the expense of extra taxation which may decrease the value of property. Thus these factors should be considered. I include disequilibrium factors used by Clark and Nieves, such as unemployment rates and cost-of-living indexes, to differentiate the different urban areas studied.

Model of Estimation

I begin with the model set forth by Roback (1982) and then by Hoehn et al. The latter used the utility function $U = U(x, s, L)$ and set up a system of equations that had to be solved for an interregional equilibrium:

$$u^0 = v\ (w - tr^*, p_a; s) \qquad (1)$$
$$u^0 = v\ (w - tr, p_r; s) \qquad (2)$$
$$N = \int_0^{r^*}(2\pi r/L_r)\ dr \qquad (3)$$
$$1 = g\ (s, N)\ c(w) \qquad (4)$$

where u^0 is the equilibrium level of utility obtained by each individual;
$v\,()$ is the maximized utility function;
w is the local wage;
t is the rate of earnings lost per unit of distance commuting to the central business district (CBD);

r is the distance from the CBD;
r^* is the radius of the urban area;
p_a is the price of land at the rural-urban fringe;
p_r is the price of land at distance r from the CBD;
N is the total population within the urban area;
L_r is the residential land purchased at distance r from the CBD; and
$g(s, N)c(w)$ is the firm's unit cost function.

Totally differentiating this system of equations and substituting to examine the amenity vector s, Hoehn et al. found that the marginal value of s at any given point r is:

$$f_r = v_s/v_w = k_r dq_r/ds - dw/ds \tag{5}$$

where k_r is the quantity of housing purchased and q_r is the product price of the local good, both at distance r from the CBD. This equation shows the positive versus negative effect of the amenity on housing prices and wages, respectively.

For both the housing and wage equations to be estimated, I explore several different models, such as the semi-log and log-linear models. Clark and Nieves used the latter due to the certainty of the restrictions it places on the implicit price function, as opposed to the semi-log or limited Box-Cox models. For both model formats, the dependent variable for the housing price differential equation is the log of the monthly rental price paid for housing, including utility costs. The dependent variable for the wage differential equation is the log of the computed hourly wage rate derived from the individual's combined wage, salary and self-employment income. Although not mentioned by Hoehn et al. or by Clark and Nieves, I use the Heckman model to correct for selection bias within the wage equation. For this purpose, I use the marital status and number of children borne by the respondent, as well as the characteristics of the individual listed below.

Variables

The following variables and definitions are included as independent variables within the housing price and wage equations.

Wage Equation:

Years of education	Highest year of school attended
Experience	Age minus education minus six years
Experience sq	Experience variable squared
In school	Dummy variable for being enrolled in school
Sex	Dummy variable for being female
Speak English	Dummy variable for being able to speak English well
White	Dummy variable for being white
Veteran status	Dummy variable for being a veteran of any era
Full-time	Dummy variable for working more than 39 hours per week
Self-employed	Dummy variable for being self-employed
Occupation	Five dummy variables for occupations: managerial and professional; service; operators and laborers; technical, sales and support; precision craft and repair; omitting farming and fishing
Industry	Eleven dummy variables for industries: construction; entertainment and recreation; business and repair; mining; agriculture, forestry and fisheries; public administration; professional services; wholesale and retail trade; transportation, communications and utilities; finance, insurance and real estate; personal services; omitting manufacturing

Housing price equation:

Bedrooms	Number of bedrooms
Other rooms	Number of total rooms minus bedrooms
Building age	Median of building age intervals in years
Condo	Dummy variable for being a condo
Detached	Dummy variable for being a detached single-family house
Kitchen	Dummy variable for having kitchen facilities
Plumbing	Dummy variable for having complete plumbing facilities
Sewage	Dummy variable for having access to public sewers
Water	Dummy variable for being serviced by public system or private company
Acreage	Dummy variable for having less than 1-acre lot

The following variables are utilized as independent factors in both equations to account for differences in areas of residence:

Separating Factors:

Census	Dummies for eight different Census divisions; omitting the East North Central division
COLI	Cost-of-living index, excluding the housing component
Unemployed	Percentage of labor force unemployed in the region or in SMSA
Vacancy	Percentage of vacant year-round housing units in the region or in SMSA (used only in housing equation)
Manufacturing	Percentage of total labor force employed in manufacturing in the region or in SMSA
Coastline	Dummy variable for bordering an ocean or the Great Lakes
Central city	Dummy variable for living or working within the area's central city
Local taxes	1977(87) per capita local taxes in the county or counties of the SMSA
Intergov rev	1977(87) per capita county revenue from intergovernmental sources
Property taxes	1977(87) per capita county revenue from property taxes
Pop density	Population per square mile
Commute time	Mean commuting time calculated for each SMSA from the individuals polled

(Dis)Amenities:

Precipitation	Thirty-year average for annual inches of precipitation
Heating degree days	Thirty-year average for yearly heating degree-days (measuring the number of degrees that each day's mean temperature is below 65 degrees Fahrenheit)
Cooling degree days	Thirty-year average for yearly cooling degree-days (measuring the opposite of above)
Windspeed	Yearly average wind speed
Sunshine	Percentage of potential sunlight realized
Humidity	Yearly average relative humidity in the afternoon
T-P ratio	Teacher-pupil ratio for all non-collegiate schools enrolling over 5000 students
Superfund	Number of Superfund sites
TSP	Average amount of total suspended particulate in air
Murder	Yearly number of murders reported per 100,000 population
Rape	Yearly number of rapes reported per 100,000 population
Robbery	Yearly number of robberies reported per 100,000 population
Agg assault	Yearly number of aggravated assaults reported per 100,000 population
Burglary	Yearly number of burglaries reported per 100,000 population
Larceny	Yearly number of larcenies reported per 100,000 population
Auto theft	Yearly number of automobile thefts reported per 100,000 population

Violent crimes	Yearly number of violent crimes reported per 100,000 population
Property crimes	Yearly number of property crimes reported per 100,000 population

These variables are measured at either the SMSA or county level. The latter are combined or averaged on a population-weighted scale, when necessary, to yield the SMSA figures, using the counties delineated by the Census for each metropolitan area.

These variables originate from a variety of sources. The cost-of-living index was obtained from the American Chamber of Commerce Researchers Association (ACCRA) which accumulates and publishes this information quarterly for major metropolitan areas. I used information from the County and City Data Book, which is published every five years, to derive the variables for the area manufacturing, unemployment and vacancy percentages; the finance variables for local taxes, property taxes and intergovernmental revenue; population density; and the teacher-pupil ratio. I obtained detailed climatic data from a publication of the National Oceanic and Atmospheric Administration for the six weather variables, including precipitation, heating and cooling degree-days, sunshine, humidity and windspeed. Upon request, the Environmental Protection Agency provided computer files with information by county for the variables for Superfund sites and TSP. The crime data I use came from a data set used with other research, but originated from the Uniform Crime Reports (UCR) issued by the Federal Bureau of Investigation. This data includes only the crimes that are reported to the police, and not the actual number of crimes committed. The UCR data are used regularly by researchers, even with this bias present, because these official statistics are one way to link known risks with the fear of crime that may be experienced by individuals or by households, as examined by Ferraro (1995).

For the housing price equation, I use observations only for renters. Information for homeowners is also available, but I believe the true annual housing price is probably best represented by renters. They are more mobile, and their rent may change more often. Thus their reported housing prices are probably more accurate. The rental housing prices I use include the annual costs of the utilities as a gross rental amount. The homeowners report the actual mortgage payments made, but no information is available on the terms of the mortgage, such as interest rate, length of term or amount of down payment. Therefore this information is difficult to use to determine the true value of the annual housing costs. Clark and Nieves (1994) used only homeowners, and Hoehn et al. (1987) used both renters and homeowners. They imputed an annual housing price using the value of the home as estimated by the homeowner. Because I believe many homeowners will not know the true value of their home, and thus perhaps introduce measurement error into the data being used, I use only renters.

CHAPTER III

DATA PREPARATION

Data Source

For the data on specific individuals and households, I utilize Census data obtained from the *Integrated Public Use Microdata Series* (IPUMS) constructed by Ruggles and Sobek (1997). I use this data series for several reasons. It is free for academics via the World Wide Web. The user can select the information to be received in a format also delineated by the user. Most importantly, the site providers combine information from different Census years into a comparable format. This process must be completed by any researcher undertaking comparison of multiple decades of Census data. The questions and wording used by each Census questionnaire vary from decade to decade. For example, the 1980 Census asked whether a respondent's housing had central air conditioning; the 1990 Census did not. Therefore this attribute of housing is not comparable across these years. Other questions may vary more in the content of the answers available for selection.

Exclusion of Observations

I begin my analysis with a 1-in-200 nationally representative sample provided by IPUMS. Even with the IPUMS consolidation across different Census years, I must further prepare some of the data. I eliminate any observations for which the respondent does not answer a question that I use in the data analysis. IPUMS attempts to fill in many of these missing items based upon a logical deduction procedure, subsequently marking these observations as being altered. I choose to use only those respondents specifically answering all pertinent questions. I assume that no systematic biases exist for why some questions are not answered by some individuals or households that will skew my results. For the same reason, I eliminate any observations for which IPUMS changes a response due to logical inconsistency.

For the housing equation, I exclude any observations denoting farm ownership. The returns to farmland and residential land use will be very different. I am interested in how crime rates will affect the marginal property landowner, which will be the "common" landowner or renter here. For the Building Age variable, the responses are stratified. The possible answers are 0-1 year old, 2-5 years old, 6-10, 11-20, 21-30, 31-40, 41-50 (41+ in 1980), and 51+ (in 1990 only). I recode this variable as the median value of each stratification interval, as Clark and Nieves (1994) did. For the 41+ interval, I use the value of 45. For the 51+ interval, I use the value of 55. Clark and Nieves did not describe how they treat this top category, and Hoehn et al. (1987) did not use this variable. I run the major regressions for the housing equation, to be discussed later, without these topcoded observations to check for any deleterious effect of this choice and find that the coefficients and significance change very little for any variables, including the Building Age variable and all crime categories. These alternate regressions use approximately 5,000 less observations. I can topcode each year equivalently or eliminate these observations, but I choose to utilize as much information as possible. Descriptive statistics for the rent equation for the total sample and by year are given in Tables 1 and 2, respectively.

For the wage equation, I use workers aged 16+ with an income greater than $2.50 per hour and less than $300 per hour in 1990 dollars for the year. I use the Consumer Price Index multiple of 1.72 supplied by IPUMS to transform 1980 dollar figures into 1990 terms for this purpose. I calculate the hourly wage by dividing the reported yearly wage and self-employment income by the annual number of hours worked. I obtain the annual hours figure by multiplying the reported average hours worked per week by the number of weeks worked. I use the lower and higher real wage cut-off amounts to reduce the possibility of miscoded responses. These wage equation restrictions are commonplace in the economic labor literature, as seen in Hersch and Stratton (1997).

Hersch and Stratton did not use a topcode for hourly wage, but I exclude these relatively few observations because some hourly wages are in the thousands with only a few hours worked per year. These observations are either miscoded or so far from the "average" worker that I fear their inclusion could cause misspecification of some variables. I initially include these observations and find no impact on the basic determinants of the wage equation. I also include all workers up to the age of 90 although Hersch included those only through the age of 65. I do initial selection bias tests on the wage equation, to be described later, with individuals below the age of 55 and then with the entire sample. I find no significant changes in coefficient sign or significance in the basic wage determinants, so I include all such workers. In these decades, many workers in this age range are actively involved in the workplace and their choices should be considered in a nationwide sample. Their impact will be limited by the small number of observations, as can be seen for the Age variable quartiles in the descriptive statistics for the wage equation in Tables 3 and 4.

As with the rent equation, I recode some variables provided by IPUMS for the wage equation. For the Speak English dummy variable, I include all those individuals self-proclaiming that they speak English well or better. For the Full-time dummy variable, I include all individuals reporting over 39 hours as their average number of hours worked per week. This choice is fashioned after the work of Clark and Nieves. Other researchers have considered fewer hours as full-time work. In the regressions to be considered, I also run them considering any work over and including 35 hours as full-time duty. The sign and significance does not change significantly for any variables besides the Full-time dummy. Its coefficient usually becomes twice as large with the change.

Because actual work history is not available from the Census data, I calculate the Experience variable or potential years of work experience as age - education - 6 years. This practice is common in the economic labor literature, as seen in Hersch (1998). I recode the variable showing the years of education because the possible responses are stratified. The intervals available are 0 years; grades 1-4; grades 5-8; grades 9, 10, 11 and 12; some years of college; and 4+ years of college. I code these intervals, respectively, as 0, 2.5, 6.5, 9, 10, 11, 12, 14, and 16 years of education. The last two categories are the most troublesome because the actual number of years of higher education are not known, but my delineation seems as appropriate as any other choice.

Verification of Labor Model

Although this research is not an exercise in the economic labor literature, I take measures to ensure that the wage equations used conform to common practice. I begin with the utilization of a two-step Heckman selection method. I only use observations of workers in my research, so I verify that the observed hourly wage rate is not biased by the exclusion of non-workers. I use the basic hedonic wage equation described above, and I use the marital status and number of children as variables, accompanied with the factors affecting wage, to proxy for the opportunity cost of working. I test the men and women separately, even though the labor literature is usually only troubled by the decision of women. These extra two variables have been shown to notably affect the reservation wage of women, and to affect men's choice little.

The Heckman technique does not exhibit a bias affecting the variable estimates. For example, I compare a log-linear regression for 1990 for men and women separately to a combined sample using regional dummy variables and the same variables described in Table 13. I obtain a correlation coefficient ρ for women of -0.060 and for men of -0.072. The standard error of the residual in the wage equation is 0.467 and 0.490, respectively, for the women and men. Both ρ are near 0, which suggests that the actual estimation equation is not producing biased results. I use the same Heckman selection model to test for alternative model formulations, such as using a semi-log model or metropolitan area dummy variables, and obtain similar results.

Choice of Functional Form

This finding verifies that the estimates found using these standard regression techniques are not biased by the exclusion of non-workers. It does not, however, yield the best model for these regressions. Hersch and Stratton (1997) used a semi-log regression model where the dependent variable was the log of the hourly wage rate. I explore the use of both semi-log and log-linear models. Hoehn et al. (1987) used a limited Box-Cox model for their wage equation. They found the best functional form to include a linear format for the independent variables and a $\lambda = 0.1$. This λ puts the dependent variable very near to a logged form.

Clark and Nieves (1994) advocated the use of the log-linear model due to the more restrictive nature of the semi-log format on the shape of the implicit price function. With their data, they found a better fit with the Box-Cox model than with the log-linear or semi-log models, but did not use it. They cited their hesitancy with utilizing the complex elasticities that can result from the nonlinear transformations and the nonconformities that can result from using different Box-Cox techniques. Hoehn et al. also assumed the same δ for each of the independent variables. Correctly allowing for different λ and δ for each model and independent variable complicates comparing the results of different specifications, due to the difficulty in computing similar dollar values for the effects of variables. For these reasons, I compare the results with the log-linear and semi-log models for both the wage and housing price equations.

Hersch (1998) recognized that assigning an injury rate to all workers within the same industry or occupation would cause the regression residuals to be correlated across these workers. I assign the same values for the (dis)amenities and separating factors to every household and individual within the same metropolitan area. She used robust or Huber/White standard errors to correct for this correlation. I use the same choice for both the rent and wage equations.

Another problem with standard errors can occur if steps are not taken to account for the weighting scheme used by the Census to select individuals to be polled. The Census uses a flat sample in 1980 such that each observation represents a fixed number of persons in the general sample for the nation. The 1990 Census uses a weighted sample to concentrate selection in certain areas or on certain types of individuals. It provides variables that quantify the weights. I correct for this weighting scheme by discounting the effect of individual observations based upon their probability of being selected. Even the 1980 factors are discounted because some individuals are selected to answer certain questions, while others are not. This technique gives me confidence that my separate regressions, to be discussed later, yield results for a nationally random sample over metropolitan areas.

I concentrate my efforts on the wage equation with the inclusion of both men and women in the regressions. Men and women can have different functional forms in their wage determinations. This distinction can be due to separate abilities or concerns, or to different concentrations within occupations, as seen in Table 5. Hersch and Stratton (1997) also corrected for possible sample selection bias for women and found that the results without the correction were essentially the same. I do compare some regressions with men and women handled separately, as seen in Table 20 which will be discussed more later in the text. However the dollar amounts that I want to obtain for the crime variables must be estimated at the household level. Combining separate valuations of these variables for men and women is difficult, as will also be discussed more later in the text. Because I find no sample selection bias and since the individual gender valuation of the dis(amenity) variables is not my priority and may actually impede my research purposes, I primarily use the wage regressions with men and women combined.

Variable Aggregation

The dis(amenity) variables are included within both the wage and housing price equations. Some of these variables, such as for climate, are measured at the level of the metropolitan area, so they do not have to be aggregated. The cost-of-living index (COLI) is also measured at the SMSA level. I use the index without the housing component, as calculated by the American Chamber of Commerce Researchers Association - ACCRA (1980, 1990) and as used by Clark and Nieves (1994). The weights for the housing component are different for 1980 and 1990; the base is 75 and 78, respectively. I multiply the 1980 figures by 1.04 to have the same base of 78 for both years.

Some variables, such as the crime rates, population density and fiscal factors, are measured at the county level on a per capita basis. I aggregate them for each year for each SMSA. For the metropolitan areas comprised of more than one county, I combine these individual county-level figures on a population-weighted scale to yield one per capita factor that is used for every person and household in that urban area. The environmental variables and teacher-pupil ratio are measured at the county level, but often in an ad hoc manner. For these variables, I take a straight average of all counties for which I have figures to be used for the measurements of that SMSA. The county composition of some metropolitan areas changes from 1980 to 1990. For each decade, I calculate the variables above using the counties at that point in time.

The unemployment, vacancy and manufacturing percentages are measured at the regional level and are assigned to every SMSA within that region. For metropolitan areas spanning the boundaries of more than one region, I use straight averages of these figures for the urban area. I also later test these regressions with individual percentages calculated for each urban area. The coastline variable is determined by whether any county comprising an urban area is adjacent to an ocean or Great Lake. For the commuting variable, I account for all of the observations in the sample. I take the mean commuting time of all these workers within each urban area. I assign this figure to everyone in that area unless there exists less than ten observations; then I code the value as missing.

Clark and Nieves also used the mean for this variable, and Hoehn et al. did not use this variable at all. The mean commuting time serves as another disamenity variable for the urban area, proxying for general traffic congestion. The actual commuting time for each individual is not used because it is not available for the housing equation as multiple workers may be present in the same household and because it should affect the market prices little. It may well affect the reservation wage or housing price of an individual, but this study observes market-determined prices and assumes that proximity to greater concentrations of housing and of workplaces will already be captured in wages and housing prices, respectively. I also run the major regressions for the wage equation, to be discussed later, using the individual commuting times rather than the calculated average for the SMSA. Around one percent of the observations disappears from the sample in the log-linear regressions, as some people claim no commute time. In both the log-linear and semi-log models, no variable coefficients or significance change noticeably besides that for the Commute variable. As a general rule, the size of the coefficient, with this change, becomes one-half to one-fourth of that of the result when using the average commute time. The significance of the variable nearly triples in size with the change, although it is always significant with either the individual or average delineation. With this information and the theoretical reasoning above, I report only regression results with the Commute variable calculated as an average for each urban area.

Missing Observations

The use of the dis(amenity) variables negates the use of the entire potential sample obtained from IPUMS. If a variable is not measured for a particular urban area or for a specific year, such as with the Commute variable described above, any individual or household in that SMSA will be excluded from a regression utilizing that variable. Table 6 lists alphabetically the urban areas studied. For either 1980 or 1990, I have information available for ninety-two urban areas for the wage equation and seventy-seven for the housing equation. For this same reason, Clark and Nieves (1994) studied seventy-six urban areas. Berger et al. (1987) used one hundred eighty-five metropolitan areas from the same data set used by Hoehn et al. (1987). I assume that they were able to use more SMSAs because their amenity list is not as expansive as the one used by me and by Clark and Nieves. Alternatively a relatively small percentage of the sample will also be excluded from the log-linear regressions if they possess none of a particular variable, as the log of zero will be coded as missing. Thus these percentages of Table 6 may change slightly based upon which set of regressions I will be studying. The use of these urban areas, coupled with the data preparation process outlined above, provides base rent and wage equation samples of 21,872 and 73,245 observations, respectively.

Changes in Variables over Time

From Tables 2 and 4, my initial belief that the separate dis(amenity) variables will change in different ways from 1980 to 1990 seems justified. My goal is to use these differences to parse the effects of separate crimes. I have information available for both 1980 and 1990 for thirty-six and thirty-two urban areas, respectively, for the wage and housing equations, as well as the additional data for other specific SMSAs for one or the other year. The means and quartiles of the basic determinants of both the rent and wage equations change very little over the decade, as might be expected. The most noticeable change for each is the increase in annual hours worked for the wage equation between 1980 and 1990 and the increase in gross rent, in 1990 dollars, for the rent equation over this period.

The regional variables for manufacturing and unemployment percentages do decrease for both the wage and rent equation between 1980 and 1990 while the vacancy percentage increases. Part of these changes could be due to the regional differences in sample size over the decade. As seen in Table 7, the South Atlantic and Pacific regions are more represented in 1990 than in 1980 for individuals and households used in the wage and rent equations, respectively, while the opposite is true for the Middle Atlantic and East North Central divisions for both equations. However the manufacturing and unemployment percentages still decrease and the vacancy percentage still increases for both the rent and wage equations, even when measured at the individual SMSA level, as seen in the variables delineated with -S in Tables 2 and 4. Therefore the allotment of observations by region should not be troublesome as these regional variables show a similar pattern when measured at the SMSA level, are used primarily to account for any disequilibrium forces in 1980 or 1990, and are not the primary focus in the overall analysis.

From Tables 2 and 4, I show that the Central city variable has also decreased for both equations between these years. A large part of this decrease is probably due to the change in Census practice between these two periods of altering the composition of individuals and households polled to target previously underrepresented portions of the population. This fact might also explain why the mean population density of the urban areas studied has significantly decreased for both equations.

Few of the means or quartiles of the climate variables change significantly for either the wage or rent equations over this period. The number of heating degree-days has decreased over the decade for both equations, and the number of cooling degree-days has increased, perhaps signifying a slightly higher concentration of observations in milder climates from 1980 to 1990. The number of Superfund sites increases over time for both equations, as might be expected. Some new sites will have appeared over the decade, but many previously existing sites were not discovered until near 1990, due to more public concern and regulation. At the same time, the TSP concentration is lowered somewhat for both equations. This fact seems to coincide with tougher regulations on air emissions over the period. The change in the Coastline variable over these years is mixed between the two equations, based upon the specific metropolitan areas sampled.

As expected from my previous crime research, the individual crime statistics show much more variety in their movements in Tables 2 and 4. For both equations, the mean per capita murder, rape and larceny rates change relatively little over the decade. The per capita robbery, aggravated assault and auto theft rates increase significantly, and the burglary rate decreases, again for both equations. These changes lead to a significant increase in average violent crimes and a small decrease in mean property crimes over these two points in time, as measured by both individuals and households sampled.

The percentage changes in crime rates are even more varied. The percentage changes are over three years, i.e. from 1977 to 1980 or from 1987 to 1990. The average percentage increases for 1980 and for 1990 are nearly the same for the crime of murder for both equations, around seventeen percent. For both households and individuals, the percentage change in rape decreases slightly over this period and that for aggravated assault increases, although by different percentage amounts between the two equations. Both the rent and wage samples show a pronounced decreased percentage change in burglary and larceny over the two time periods. Larceny goes from a high to a low percentage increase for both equations between 1980 and 1990, while burglary goes from a positive to a negative percentage change. The percentage change in auto theft increases significantly between the time periods, from a small to a large positive change for the wage equation and from a large negative to a large positive change for the rent equation. This same scenario in the rent sample arises for the percentage change in robbery, while there exists little change at all from the large positive increase in both years for the wage equation.

The increases or decreases mentioned above are in the means; the quartiles show an even more pronounced difference. If I use the median percentage changes rather than the means, the results are quite similar. The one major difference is for robbery in the rent equation in 1980; it has a median change of a positive ten percent rather than a negative fourteen percent. These changes are measured directly before the years studied. Their effect should be contained in the wages and rental amounts.

CHAPTER IV

REGRESSION ANALYSIS

Basic Regressions without Dis(amenity) Variables

I begin my analysis of the rent and wage equations with the basic determinants available to me from the Census data and without the (dis)amenity variables and separating factors described above. Table 8 gives the results of both the log-linear and semi-log regressions for the rent equation. They have a R^2 of .502 and of .509, respectively. As expected, more rooms, including bedrooms, significantly increase the gross rent in both model formats. Having a detached house or condominium also significantly increases the rent paid, as opposed to not living in these types of units. Having sewage and water service provided significantly increases the returns to housing. Increasing the age of the housing unit significantly decreases the rent received, for both models. Gross rent also increases over time, as seen in the coefficient of the Time dummy variable. This would be expected since it is in nominal terms. The reason for leaving rent in these terms will be explored more later in the analysis of other regressions. Having complete plumbing facilities significantly increases the gross rent, but possessing kitchen facilities does not. Possessing less than an acre decreases the rent for a housing unit in both models, although insignificantly.

I do not report the individual effects of the regions within Table 8 for the sake of brevity. For both the log-linear and semi-log models, all regional dummy variables are statistically significant, except for the West South Central division. The East North

Central division is omitted within the regressions to avoid perfect collinearity. For both models, the New England, Middle Atlantic, South Atlantic, Mountain and Pacific divisions have positive coefficients, and the West North Central, East South Central and West South Central divisions are negative. The East South Central and Pacific regions have the largest coefficients of each group compared to the omitted East North Central division.

Table 9 gives the results of the log-linear and semi-log regressions for the wage equation. They have a R^2 of .448 and of .467, respectively. Many of the variables have the same expected effect for both model formats. Having more years of education, having more experience, being able to speak English and being white all significantly increase the hourly wage. These results are usually found within the labor economics literature. Being self-employed and a veteran also increases the wage. The Time dummy variable increases the wage because it is measured in nominal terms, which will again be discussed more further in the text.

Experience squared is only measured in the semi-log regression, since taking the log of this figure within the log-linear model will make it a multiple of the Experience variable. The Experience squared variable is significantly negative, showing decreasing returns to experience. I also include this variable within the log-linear model, without being logged, and exclude it from the semi-log model in all of the major regressions, to be discussed later, to verify that its inclusion or exclusion is not driving any results. No variables experience a significant change in coefficient or significance level in any regressions with these changes.

Being female significantly decreases the hourly wage paid, as does being in school at the time. Both of these effects are common in the economic labor literature. Being a full-time worker significantly decreases the hourly wage in both models. This result may seem counterintuitive, but this effect may be proxying for the level of benefits that a worker receives. No such information is available from the Census data, but I expect a full-time worker to be compensated more in benefits, and perhaps somewhat less in pay, than a part-time worker.

I do not report the individual effects of the regions within Table 9. For both the log-linear and semi-log models, all regional dummy variables are statistically significant, except for the New England and Middle Atlantic divisions. All regions have a negative impact compared to the omitted East North Central division, except for the Middle Atlantic and Pacific regions. The East South Central division has the largest coefficient for both models.

I also do not report the individual effects of the occupational and industry dummy variables within Table 9 for the sake of brevity. For both the log-linear and semi-log models, all occupations have a significant positive effect on wages compared to the base occupational category of farming and fishing, which is omitted from the regression equations to avoid perfect collinearity. Managerial and professional jobs have the greatest coefficient. For the log-linear model, all industry dummy variables have negative coefficients compared to the omitted category of manufacturing, except for the mining, transportation and public administration categories. The same is true for the semi-log model, except that the public administration category is also negative, although insignificant. Both models have the trade industry with the largest coefficient in absolute value. These omitted categories are the same as those chosen by Clark and Nieves (1994).

Table 10 reports the results of the same log-linear and semi-log regressions for the rent equation as Table 8, except that metropolitan area dummy variables are used in place of regional dummies. The R^2 for the two regressions increase slightly from using regional dummy variables to .553 and to .558, respectively. The only noticeable differences are that the Acreage and Kitchen variables have become significant at the five percent level in the log-linear model. Table 11 replaces the regional dummy variables of the wage equations of Table 9 with the metropolitan area dummy variables. Again the R^2 increase slightly to .461 for the log-linear regression and to .479 for the semi-log regression. No major differences arise in coefficients or significance with this change. I do not report the individual effects of the metropolitan area dummy variables for either model due to the extremely large number involved.

Tables 8-11 are based on restricted samples that anticipate the smaller sample sizes we will experience once the (dis)amenity variables are included. Although not reported here, I also ran the same models for Tables 8-11 on the full sample of cases. These alternative regressions use approximately 53,000 and 141,000 observations for the rent and wage equations, respectively. The number of urban areas delineated expands to one-hundred seventy SMSAs, compared to the base regressions of Tables 8-11.

The descriptive statistics for the rent and wage equations for this larger sample are very similar to those found in Tables 1 and 3, both for the basic determinants of the equations and for all other variables to be included in later regressions. Using the extra observations for the basic wage regressions of Tables 9 and 11 does not change the coefficient or significance of any variables to any significant degree, in either the log-linear or semi-log models. Only two variables are affected in the rent regressions of Tables 8 and 10 with the addition of these observations. The Acreage variable has become positive in three of the four rent regressions, although significant in only one of them. The Kitchen variable has become positive in the two semi-log regressions, but the coefficients are both insignificant. The consistency of the results with a larger and more dispersed sample provides confidence that the sample I use will yield representative nationwide results.

Log-linear Regressions with Dis(amenity) Variables and Index Crimes

Analysis of Housing Equation

Table 12 extends the log-linear regression of Table 8 for the rent equation by adding the (dis)amenity variables and separating factors. These additions increase the R^2 from .502 to .540. It should be noted that most of the basic determinants of the rent equation change very little in the way of coefficient sign or significance. Only the Kitchen variable really changes by becoming significantly negative. Tables 12 and 16 give the variable means for the log-linear and semi-log regressions, respectively, and show only a very small percentage of observations without the kitchen and plumbing features. This fact may explain the insignificance of the Kitchen variable in Tables 8 and 10 because the kitchen's effect may be consumed by the plumbing feature. I run the regressions of Tables 12 and 16, with the (dis)amenities and separating factors included, without kitchen or plumbing facilities and find no significant difference in any of the variables' coefficients or significance for either model. I do include these two variables in all of the regressions studied to account for as many characteristics of housing as possible.

Of the separating factors, all of the variables are significant at the five-percent level, and most of the results are intuitive. The cost-of-living index increases the gross rent, and a higher vacancy rate reduces it. Higher concentrations of manufacturing employment reduce the value of housing. A greater population density increases the gross rent paid. This variable may proxy for the urban amenities that accompany higher densities, such as a bigger and better selection of restaurants. This result may coincide with the Central city variable reducing gross rent, showing renters' dislike for living within this population density. The Unemployment variable is positive although I would expect it to decrease rent to coax more households to live among unemployed persons. Alternative delineations of this variable will be analyzed later to address this issue. The Commute variable also seems counterintuitive as people are paying more rent for increased transit time. These last two variables are the only ones in this category that differ from the findings of Clark and Nieves (1994).

The fiscal factors may be more difficult to discern. The effect of increased per capita property taxes is to significantly decrease the gross rent paid. Initially I would expect part of these higher taxes to be passed on to the renters. At the same time increased per capita local taxes significantly increase housing costs. Clark and Nieves found a negative impact from local taxation. Higher taxes can reduce the demand for living in that area, so rents would be lower. If this is the case, my property tax variable may be capturing this effect. Increasing per capita intergovernmental revenue significantly decreases rent paid. One might expect higher levels of spending from state and federal sources to benefit renters in some way. Clark and Nieves, who found the same negative effect, attributed it to higher spending on poverty within the region, which is not attractive for housing.

Most of the (dis)amenity variables meet expectations. Being near a coast significantly increases gross rent paid, as it is an amenity. Households will pay more in housing costs for more of an amenity. An increase in the number of either heating or cooling degree-days significantly decreases rent, as the marginal household prefers moderate temperatures and lower heating and cooling costs. The amenity sunshine significantly increases gross rent, and the disamenity humidity decreases it, although not significantly. I find that average windspeed and precipitation significantly decrease rent, making them disamenities. These two variables are less obvious as being amenities or disamenities for the marginal household. Their attractiveness probably depends more upon the amount present in the household's area than some of the other (dis)amenity variables. The results of Clark and Nieves and of Hoehn et al. for the housing equation classified precipitation as a disamenity and windspeed as an amenity. The teacher-pupil ratio also classifies as an amenity, significantly increasing rent. The environmental variables measuring the number of Superfund sites and the amount of TSP are misclassified as amenities. Both increase the amount of rent paid, although only the Superfund variable is significant. Table 12 measures the crime variables as index numbers for per capita violent and property crimes. Both indexes significantly decrease gross rent paid, making them disamenities.

Derivation of Costs

The last column of Table 12, labeled "DIFF" for "differential," attaches an annual dollar amount to an increase in the described variable. A negative amount signifies how much the household would have to be compensated to accept more. These figures represent the amount paid for a ten percent increase in the discrete variables and a change from zero to one for the dummy variables. With a log-linear regression, I do not use the variable means to calculate the differentials in the last column. They are provided solely to give the reader a basis point for judgment. For a discrete variable in this model, the coefficient gives the percentage change in the gross rent for a percentage change in the independent variable. The dollar amount comes from multiplying the coefficient by one-tenth by the average yearly rental amount to determine a change of ten percent in the variable. I do a similar transformation for the dummy variables for a change from zero to one.

The dollar amount can be equated to 1985 dollar terms, although technically the amount is in a combination of 1980 and 1990 dollars. I choose to leave all dollar amounts in nominal terms in the regressions although I could transform all such amounts to the same base year. I have a CPI index provided by IPUMS. I do not believe the same multiple should necessarily be used for normalizing rental amounts and tax and revenue figures. Later within the text I will be including the results from the wage equation, so I will also have to use an index number for wages. Any choice I make with these index numbers will have costs and benefits. Transforming variables delineated in 1980 dollars into 1990 terms does not affect the size or significance of any coefficient at all, other than that for the time dummy variable, for the log-linear model and minimally for the semi-log model. However this transformation will affect the means of the variables used as a basis for the log-linear regressions and for computation of dollar amounts in the semi-log regressions, as will be explained more later. Because the different model specifications use varying amounts of observations between 1980 and 1990 which could involve sample selection bias and for the other reasons listed above, I choose to keep the dollar amounts in nominal terms and allow the time dummy variable to capture changes in rents or wages from 1980 to 1990.

The dollar figures are very interesting. For example, the variable for the number of bedrooms shows a significant coefficient of 0.145 with a sample mean of 2.85 bedrooms per home. For increasing their number of bedrooms by ten percent, or by .285 rooms at the average, households are willing to pay $69.32 per year. If this marginal calculation were valid further from the mean, households would be willing to pay over $243 more per year for an extra bedroom. This compares to the average annual rental cost of housing for this sample of $4774 in 1980-90 dollars, or a five percent increase. Similarly the data show that a household would be willing to pay over $937 per year to live in a single-family home detached from other residences. These figures seem credible. The articles by Hoehn et al. (1987) and by Clark and Nieves (1994) did not present the dollar figures for non-amenity variables, so a direct comparison is not possible.

Any of the variables with the wrong coefficient sign will have an incorrect dollar amount the households will bear. This example shows why researchers have argued that both housing and wage equations should be used to evaluate (dis)amenity variables. These same (dis)amenities will be included in the wage equation. The total effect will be derived from both equations. Superfund sites are misclassified as an amenity in the rent equation of Table 12. If the coefficient is of the correct sign and of enough magnitude for this variable in the wage equation, the total effect will be of the correct sign.

We should have the most confidence in the results for the variables with the correct sign and significance in both the housing and wage equations. The only other practical way to determine whether the combined effect is significant is to assume that the covariance terms between the rent and wage equations are zero. If true, I could add the standard errors from the individual equations and use the sum to determine the significance. I do not believe that the assumption of zero covariance necessarily holds. Therefore throughout the text, I will check the significance of the results from each individual equation and not the significance of the combined total effect.

Some results may need special consideration even with a correctly signed coefficient and statistical significance. From Table 12, I find that adding plumbing to a home will be worth over $2000 annually in 1985 terms. This amount is a very large percentage of the average rental amount, but only a very small percentage of the sample, less than one percent polled, does not have plumbing. I use the sample means for these calculations, but some variables may need to be calculated at another point to make more economic sense. Individuals or households at levels far from the mean will theoretically value more or less of that variable than this marginal calculation will show. Later I will address this type of issue more in terms of income levels for the rent and wage equations.

The crime figures are appealing in this regression. Households should be compensated $40 and $48 annually if the number of violent and property crimes, respectively, increases by ten percent. Alternatively each household would be willing to pay these amounts to reduce such crimes in their area by this percentage. These dollar amounts should be evaluated at the mean for the nationwide sample. These amounts will probably be different in high- versus low-crime areas. These amounts also do not account for the effect crime has on the wages of the household members.

Analysis of Wage Equation

Table 13 gives the equivalent results for the wage equation using the same log-linear regression with regional dummy variables. The R^2 has increased to .459 from .448 when using only the basic determinants. These variables have changed very little in size of coefficient or significance from Table 9. The cost-of-living index significantly increases the hourly wage, as would be expected. Working within a central city also significantly increases an individual's wage. A higher regional unemployment percentage significantly increases the wage rate. This may seem counterintuitive, but Clark and Nieves (1994) found the same positive effect. The variables for population density and for regional manufacturing percentage are both insignificant.

The effect of the fiscal factors is again mixed. Higher local taxes significantly increase the wage, which is intuitive if I believe that workers must be compensated for bearing this increased taxation over other areas where they could work. Property taxes, however, decrease the hourly wage. County revenue from state and federal transfers significantly decreases wages. Clark and Nieves found this same effect, attributing it to workers desiring spending from outside sources.

The (dis)amenity variables are not always significant or of the correct sign in the rent equation in Table 13. The variables for teacher-pupil ratio, humidity, cooling degree-days and TSP are all insignificant, and the first three are of the wrong sign. Precipitation significantly decreases the wage, classifying it as an amenity. Of the remaining variables, Superfund sites, heating degree-days and commuting time are significantly classified correctly as disamenities. The sunshine and coastline variables are significantly misclassified as disamenities, while windspeed and the index measures for violent and property crimes are misclassified as amenities.

Once again I calculate the value of increasing the discrete variables by ten percent and changing the dummy variables from zero to one. The means for the (dis)amenity variables and separating factors may be different from those found in Table 12. This occurs because the sample size is larger for the wage equation and because the people being polled are not necessarily the same within the two samples. In fact there may be very little cross-sampling. This makes no theoretical difference as both samples span urban areas across the United States. With a random sample, I am calculating the impact felt by the marginal household or worker in the United States.

The dollar amounts are expressed per household rather than per worker for easy comparison with Table 12. To obtain these dollar amounts, I do use the average hourly wage and number of hours worked per year for this particular sample. They are $11.94 in 1980-90 terms and 1,946 annual hours. I also use the average number of workers in each household polled for each worker in the wage equation sample. This number will be slightly different for each sample depending upon the people polled. The average for all of the wage equation regressions to be performed is near 1.3 workers per household. With this set of factors, I calculate the household differential found in the last column of Table 13. For a change of ten percent to match the earlier analysis, I multiply the coefficient by one-tenth by the mean hourly wage by the number of hours worked annually per worker by the number of workers per household. I do a similar transformation for the dummy variables.

I could use a variety of formulas for calculating the dollar differentials in these regressions I examine. By examining ten percent changes per household, the resulting dollar differentials will be directly comparable. In the top portion of Table 30, I combine the dollar figures of Tables 12 and 13 for the crime indexes. In Tables 30 and 31, the sign of the housing component will be switched from that found in the original regressions, such as for Table 12. Tables 30 and 31 are intended to show the costs of crimes to individuals and to households. A negative sign on a crime variable in the rent regressions signifies that the variable is a disamenity, which will have a positive cost. However a positive sign on a crime variable in the wage regressions signifies that the variable is a disamenity with a positive cost, so the same sign is used in Table 30 and 31 for the wage component as in the original regression results.

As can be seen, the total effect is that households do not experience any positive costs from increases in either violent or property index crimes. By examining only the rental housing equation, I would reach the opposite conclusion. The results of Hoehn et al. (1987) and of Clark and Nieves (1994) did not support this finding. They both used only an index measure of violent crime in their regressions and found a disamenity effect present. I discuss this difference in results more later in the conclusion.

Location Dummy Variables

To test for possible differences arising in any results due to the choice of location dummy variables, I use Table 14 to compare with the log-linear regression of Table 12. This new table replaces the regional dummy variables with those of individual metropolitan areas. The R^2 increases from .540 to .559. The coefficients and significance change minimally for all of the basic determinants of the rent equation. In fact, the dollar differentials presented in the last column are almost exactly the same as those in Table 12.

While these results are reassuring, those for the most of the (dis)amenities and separating factors are not. Whereas before only the variables for TSP and humidity were insignificant with the regional dummy variables, now most of the others are insignificant. This trend includes the variables for the cost-of-living index, vacancy rate, violent and property crimes, coastline, population density, Superfund sites, TSP, heating and cooling degree-days, precipitation, windspeed, humidity, teacher-pupil ratio and intergovernmental revenue. The metropolitan area dummy variables do not seem to fit the data well with this type of regression, as seen with the poor performance of most of the variables mentioned above and by the high dollar differential that is attributed to the coastline variable.

Table 15 does the same comparison for the log-linear regression of the wage equation. Including the metropolitan area dummy variables increases the R^2 relatively little from .459 to .463. Once again the coefficients, significance and resulting dollar differentials of the basic determinants of the wage equation have changed hardly at all with this change in the location dummy variables. However the variables for the cost-of-living index, unemployment rate, property crime index, all environmental and climate factors, commuting time, teacher-pupil ratio, intergovernmental revenue and property taxes are all insignificant. The differential for the coastline variable takes on an even greater size with this wage equation. These types of results, with some variables like the basic determinants being affected very little while other variables, such as for coastline, are greatly affected, may suggest some problems with collinearity. Using a great number of dummy variables, as was done here when delineating specific metropolitan areas, may make the circumstances the worst possible, but such results may raise concerns that I will confront more later in the text.

Combining Housing and Wage Effects

I show the combined effect on the crime variables of these two new sets of regressions in the middle portion of Table 30. The index measure for property crimes now shows a positive annual cost for households, but the violent crime variable exhibits a very large negative amount because both the rent and wage equations have the wrong sign. Compared to the effects shown with the regional dummy variables in the top portion of the table, I find no correctly signed individual effect at the five-percent significance level, which would instill more confidence in my findings. I run the same regressions for Tables 14 and 15 without the coastline variable to check whether it is causing some collinearity problems. The coefficients and significance of every variable in both the wage and rent equations is essentially unchanged.

Semi-log Regressions

I create Tables 16-19 to perform the same regressions of Tables 12-15, except in a semi-log model format. Table 16 gives the results of the regression for the rent equation with regional dummy variables. The R^2 is. 548, compared to .509 for the basic semi-log regression and to .540 for the log-linear regression of Table 12. The results for the basic determinants of the rent equation are very similar to those found in the original semi-log regression of Table 8. The dollar differentials for the basic determinants located in the last column of Table 16 are very similar to those for the log-linear regression of Table 12. These results provide robustness in the explanatory power of these variables.

The (dis)amenities and separating factors of Table 16 do not perform as well as in the log-linear regression. The effects of the fiscal factors are the same, except that the variable for intergovernmental revenue has become positive and insignificant. The cost-of-living index also becomes insignificant. Of the (dis)amenities, the variables for violent crimes, Superfund sites, heating and cooling degree-days, precipitation, humidity, and commuting time are misclassified. The index measures for both violent and property crimes have become insignificant.

The dollar differentials per household for these two variables are both less than one dollar annually. This result is due primarily to the very low coefficients for these variables. The coefficient in the semi-log regression gives the percentage change in the dependent variable of gross rent for a unit change in the independent variable. To obtain the dollar differentials in Table 16 for the discrete variables, I multiply the coefficient by the unit change given in the column marked "10% CHANGE" by the average annual rent for the sample, which is $4780. I do a similar transformation for the dummy variables.

For property crimes, a ten percent increase from the mean equates to 597 more crime units in this sample. Because this variable is reported per 100,000 population, the differential amounts to each household paying one dollar annually to prevent one property crime per 200 population. I would expect this figure to be larger.

Table 17 gives the same semi-log regression results for the wage equation. The coefficients and significance change little from the basic regression results of Table 9. The R^2 is .477, compared to .467 for Table 9 and to .459 for Table 13. In the semi-log regression of Table 17, many of the same variables are misclassified as in the log-linear regression, including the percentage of unemployed, property crimes, coastline status, precipitation, sunshine and teacher-pupil ratio. The cost-of-living index and coastline variables also have very large differentials associated with them in both model formats. In Table 17, the violent crime variable has the correct sign, but both index crime measures are insignificant.

I combine the semi-log regression results for the crime variables of the rent and wage equations of Tables 16 and 17, respectively, in the top portion of Table 31. The measure for the violent crime index does show a combined positive cost to households, but only the wage equation has the correct sign and it is insignificant. Although one equation yields a positive cost and the other a negative cost for property crimes, just as with violent crimes, the combined effect is no positive cost to renters.

I show the semi-log regression results for the rent equation using metropolitan area dummy variables in Table 18. Almost no difference exists in the results for the basic determinants of the rent equation in Table 10. The dollar differentials in the last column of Table 18 are very similar to those of the log-linear regression of Table 14 with the metropolitan area dummy variables. The only real difference is that the Kitchen variable is insignificant in Table 18, just as it is in the semi-log regression of Table 16 with the regional dummy variables.

The use of the metropolitan area dummy variables in the semi-log regression of Table 18 yields very poor performance of most of the (dis)amenities and separating factors, just as it does in the log-linear model. Of these twenty-two variables, only seven are significant, and not all of them are classified correctly. Again the coastline variable has a large dollar differential compared to the other variables, just as it does in Table 14. The index measure for property crimes has the correct sign and significance, but the violent crime variable has neither.

Table 19 gives the results of the semi-log regression for the wage equation using the metropolitan area dummy variables. The R^2 of .481 remains essentially unchanged from .479 for the original semi-log regression of Table 11 without the (dis)amenities and separating factors. None of the coefficients or significance levels of the basic determinants has changed significantly from the original regression. As with the semi-log regression for the rent equation in Table 18, only six of the twenty-one (dis)amenities and separating factors are significant, and most of them are misclassified. The coastline variable is again afforded a very large dollar differential in this semi-log regression. Both of the crime index measures are misclassified as amenities in Table 19.

The middle portion of Table 31 gives the combined effects of the rent and wage equations for violent and property crimes using metropolitan area dummy variables. Neither shows a positive cost to households; in fact both are fairly large negative numbers. With the poor performance of these metropolitan area dummy variables, both within separate regressions and with results combined, I concentrate the rest of my efforts on using the regional dummy variables. Other researchers, such as Clark and Nieves (1994), utilized this same choice. The metropolitan area dummy variables are consuming too much of the variation existent in these samples. Individual dummies are becoming very important as they represent differences from other urban areas. While this information may be valuable in judging the overall success of attempting to parse this information from rent and wage equations, it does not help me to find the effect of crime on housing and wage decisions. If most variables are not significant, I am not gleaning much new information.

I run regressions for the rent and wage equations in the log-linear and semi-log formats without any location dummy variables to check the previous results. Few of the variables change dramatically, i.e., change the sign of the coefficient or its size by a factor of five. However this change will make the combined dollar differential of violent crime positive for the log-linear model. Neither of the combined effects for violent or property crimes will significantly change for the semi-log model without any location dummy variables. Because I believe the regional dummy variables serve a purpose in connecting separate urban areas into collective groups and since few significant changes occur in the regression results without their inclusion, I retain the use of these variables.

Sample Selection and Model Specification

Because the semi-log regression results for both the rent and wage equations are somewhat different from the log-linear regressions, I want to make sure that they are not due to the difference in sample selection from the use of normal versus logged variables.

The sample for the rent equation changes very little, from 21,831 observations for the log-linear model to 21,872 for the semi-log regression. The additional observations all come from the metropolitan area of Anchorage, AK. Running the semi-log regressions, with both regional and metropolitan area dummy variables, without these observations yields no significant change in the coefficient sign or significance of any variables.

The sample for the wage equation increases from 70,343 observations for the log-linear regression to 73,245 for the semi-log model. These observations come from a variety of urban areas. Once these observations are removed, the semi-log regressions result in the same basic coefficients and significance for all variables as they did before. The only exception is that the coastline variable has switched sign with the use of the metropolitan area dummy variables, but it is insignificant. These results show that the sample selection is not driving the differences in results between the log-linear and semi-log models.

I also return to a further analysis of the log-linear model for the wage equation of Table 13 to examine the individual effects of men and women. In Table 20 I perform the same regression with the genders separated. Thus I exclude the Sex variable. For most of the variables it is apparent that a near linear combination of the separate coefficients for the female and male regression variables of Table 20 will give the coefficients of the variables found in Table 13. For the basic determinants of the wage equation, the coefficient sign and significance do not change between the female and male counterparts, except for the sign for veteran status which is insignificant. The most noticeable differences are the size of the coefficients for the White and Full-time variables. The male coefficients are five times the size of those for female while the mean sample values for these variables are only slightly different.

The (dis)amenities and separating factors of Table 20 give very much the same type of picture. The sample means for the variables are practically the same since both sexes come from urban areas across the nation. The variables for manufacturing percentage and population density change coefficient sign between the female and male regressions, but both variables are insignificant in both regressions. Interestingly the only variables that are insignificant in Table 13 with the sexes combined are the ones in Table 20 that are insignificant for both the female and male regressions. The only variables that have sizable coefficient differences between the male and female regressions are precipitation, commuting time and teacher-pupil ratio. Each of these variables is insignificant in at least one of the regressions.

The crime indexes are misclassified as amenities in both the male and female regressions, just as they are when combined in Table 13. The results are very similar when comparing the semi-log regressions or using the metropolitan area dummy variables. Because my main research emphasis is on the crime variables and because I see no major differences in the male/female trade-off, I restrict the rest of my evaluations to regressions with the sexes combined.

I also want to verify the validity of the rent equation. New York City is notorious for its rent-control laws, for which I do not explicitly control without using the metropolitan area dummy variables. It also comprises a disproportionately large percentage of the rent equation sample for 1980, as seen in Table 6. So I run the log-linear and semi-log regressions of Tables 12 and 16, respectively with the regional dummy variables and with a dummy variable for New York City. In the log-linear model, the sign for humidity changes, but it is insignificant. The variables for property crimes and intergovernmental revenue are no longer significant. The coefficient sign and significance are virtually unchanged among the other variables.

In the semi-log model, the variables for the cost-of-living index, coastline status, violent crimes, property crimes and population density change coefficient sign with this additional variable. The last three of these variables also become significant, where before they were not. In both models, the New York City dummy variable has a significantly negative effect on gross rent. The crime effects do change with the addition of this dummy variable. However I believe they will change with specific dummy variables for any urban areas with exceptionally high or low levels of crime. This variable's use turns the property crime variable from a disamenity into a significant amenity in the semi-log model. Because the results are mixed and because I do not want to favor any specific urban area unnecessarily in this nationwide analysis, I exclude the New York City dummy variable in future regressions.

Regressions using Individual Crime Rates

Log-linear Model

I now turn to analyzing separate crime rates within this rent/wage hedonic model. I first look at Table 21 with the log-linear regression results for the rent equation using regional dummy variables and including all crime rates, rather than index measures. I include only the results for the (dis)amenities and separating factors, as the basic determinants show very much the same pattern of the previous tables. Comparison with Table 12, which includes the index crime measures, shows that only the coefficients for TSP and humidity have changed coefficient sign. Both of these variables were insignificant in one of the two regressions, so this change is not a large difference. Only five of the variables are insignificant in Table 21, and none of them are the crime measures.

The four crime variables that have positive coefficients are murder, rape, robbery and larceny. Theoretically we expect these effects to be negative to be classified as disamenities, however I expect the households to value the separate crime rates differently. With the index crimes in Table 12, both measures are negative. Because aggravated assaults comprise the largest percentage of violent crimes, the results of Tables 12 and Table 21 may be consistent since this category has a negative coefficient in Table 21. The combined negative effects of burglary and auto theft of Table 21 may explain the negative index measure for property crimes in Table 12.

Table 22 gives the log-linear results for the wage equation with all seven crime rates included. The results for all variables are similar to those of Table 13 with the index crime measures. Only the variables for precipitation and humidity have changed coefficient sign, but they are both insignificant. The dollar differentials are also comparable, especially with the large values for sunshine and a coastline afforded by workers. Table 13 has both variables for violent and property crimes misclassified as amenities. In Table 22, the crimes of murder and rape are insignificant. Of the remaining crime variables, robbery and larceny are classified correctly as disamenities.

The combination of these results for the rent and wage equations of Tables 21 and 22 are shown in the bottom portion of Table 30 under the heading of "All crimes". Three crimes - rape, robbery and larceny - have the expected positive cost to households. Robbery and larceny come from the correctly signed and significant effects of the wage equation. In fact the effects from the wage equation are the dominating forces in all results, except for murder. Larceny has the largest correctly signed effect, perhaps due at least in part to being the most prevalent crime category.

Semi-log Model

Table 23 examines the semi-log regression for the rent equation with all seven crime rates included. Compared with Table 16 for this same regression with the index crime measures, the only noticeable difference in the coefficients or significance of the remaining variables is for coastline status. Differentiating the crime rates in Table 23 significantly reduces the coefficient and significance of this variable. Thus the household's dollar differential for a coastline decreases from $146 to $9 annually.

The differences are somewhat more substantial when comparing the semi-log and log-linear regressions of Tables 23 and 21, respectively, with both including the individual crime rates. Five of the (dis)amenities or separating factors change coefficient sign in the semi-log regression, although only two do so significantly. Both heating and cooling degree-days become significantly classified as amenities. None of the crime rates change sign with the semi-log regression, but murder and auto theft are now insignificant. The dollar differentials are still comparable across Tables 21 and 23.

Table 24 has the semi-log regression results for the wage equation with all crime rates included. Essentially no difference exists with the other variables from the same regression of Table 17 using index crime variables. The only change is that the precipitation variable becomes insignificant. Compared to the log-linear regression of Table 22, the only non-crime differences that arise are that the variables for cooling degree-days and precipitation change sign in the semi-log regression, but both are insignificant. For the crime rates, aggravated assault, larceny and auto theft become insignificant in the semi-log regression. Murder changes sign, but is insignificant in both model formats. The household dollar differentials become noticeably smaller for burglary and larceny in the semi-log model.

I show the combined effects of the rent and wage equations for these semi-log regressions of Tables 23 and 24 under the heading of "All crimes" in the bottom portion of Table 31. The crimes of murder, rape, robbery and larceny show a positive annual cost to households. Of these categories, only robbery has at least one significantly and correctly signed result comprising the combined effect. Comparison with these same results for the log-linear regressions in Table 30 shows that murder now has a positive cost, but the costs for burglary and larceny are significantly decreased in the semi-log format.

Test of 1990 Results

Because my research is directed towards the effects of these individual crime rates, I use two more different types of regressions to check the validity of these results. The first tests the results for a single year. The 1990 log-linear regression for the rent equation is reported in Table 25. The number of observations is obviously much lower, and the sample means are quite different for some variables, compared to the full log-linear regression of Table 21. The population density mean is only 872 people per square mile for 1990 compared to 1664 for 1980-90. Table 6 gives some explanation for this figure. Some high-density areas such as Chicago and New York are much less represented in the 1990 sample.

This change in urban area selection is the primary reason why the average per capita fiscal factors are less in Table 25 even though they are measured in 1990 dollars, rather than the 1980-90 dollars of Table 21. The 1990 sample has fewer heating degree-days and more cooling degree-days than the combined sample, indicating more moderate temperatures. Table 7 shows this 1990 trend, as more observations are located in the Pacific and South Atlantic regions, and less in the New England and East North Central divisions. This fact explains the different means of the regional manufacturing, unemployment and vacancy rates between the two tables.

Table 25 shows that many of the location variables become insignificant when using only 1990 data, including central city status, cost-of-living index and the regional manufacturing, unemployment and vacancy percentages. Of the remaining non-crime variables, the variables for coastline and humidity have changed sign from Table 21 to be significantly classified as disamenities. It is difficult to compare the dollar differentials for these variables as the dollar amounts are measured in different base years in these tables and because the ten percent changes represent substantially different unit amounts for some variables.

For the crime variables, the sample mean has increased for 1990 compared to the 1980-90 data for all categories, except for burglary which has significantly decreased. Whereas all crime rates were significant for the total sample of Table 21, murder and auto theft have become insignificant for 1990 in Table 25. Robbery has also changed sign to become a disamenity in the new sample. Again the dollar differentials are not directly comparable, but robbery and auto theft have changed their relative importance in 1990 compared to the other crime rates.

Table 26 gives the 1990 log-linear regression results for the wage equation. Many of the same differences in sample means that I find for the rent equation exist between the 1990 and 1980-90 wage sample, although more muted. The means for the manufacturing, unemployment and vacancy percentages are different between Tables 22 and 26, but by much less than with the rent equation. The population density is also lower for the new, smaller wage sample. However the fiscal factors have all increased in the average from the 1980-90 data to the 1990 series, when they decreased for the rent equation. The sample means of all these fiscal factors are comparable between the 1990 rent and wage equation samples of Tables 25 and 26, respectively.

Between the full 1980-90 sample and the smaller 1990 data set for the wage equation, the means of the crime variables have increased, except for that of burglary, as found in the rent equation. The only real change found in the results with these variables between the two regressions is that the rape rate has become significant in the 1990 data; no crime variables have changed coefficient sign. The dollar differentials are not directly comparable, but the effect of aggravated assault has become more powerful, relative to the other variables, in Table 26. I used these smaller samples, which transformed the limited panel data to OLS regressions for a single period, to show that the previous results are not due strictly to the panel data aspect, especially for the crime variables. I feel more confident in the use of the 1980-90 data due to the use of more urban areas and to the changing valuation of multiple metropolitan areas.

Test of Selection Bias

Due to the effect that eliminating part of the sample has on some variables, I choose to test this more thoroughly on the basic log-linear regressions of Tables 21 and 22. Table 27 tests the effect several key variables have on the regression results of the rent equation. Many individual observations are eliminated from the full sample by the inclusion of the Central city variable because some respondents do not mark whether they live or work in this area, so that variable is marked as missing. Entire metropolitan areas, and their accompanying observations, are excluded by the use of the variables for the cost-of-living index and commuting time. ACCRA does not compute the COLI for some urban areas, and enough observations were not present to calculate a mean commuting time for some metropolitan areas. Table 27 tests the log-linear regression for the rent equation of Table 21 without these variables. The number of observations increases from 21,831 to 41,179.

The variable means change very little, much less so than when halving the sample of Table 21 by including only 1990 data. Excluding these three variables changes the coefficient sign of the variables for TSP, windspeed and humidity, but they are all insignificant. The dollar differentials are very comparable across Tables 21 and 27, although the amounts for coastline, sunshine and teacher-pupil ratio have changed somewhat percentage-wise. The crime figures are also very similar between these regressions. The only coefficient or significance change occurs for the rape variable, which becomes insignificant with the extra observations. The dollar differentials are very comparable, although burglary has changed the most.

Table 28 has the results for the log-linear regression for the wage equation without the variables for central city status, cost-of-living index and commuting time. The number of observations increases from 70,343 in Table 22 to 103,005 for this regression. The variable means are similar, except for population density and for the three fiscal factors, which have all increased. Five of the non-crime variables have changed coefficient sign from the regression with the smaller sample, but four of these are insignificant in one of the regressions. The dollar differentials are comparable, except for the variables that have changed sign and for the sunshine and coastline variables whose effects are more muted now.

The results for the crime variables do change somewhat. Murder and auto theft change sign with the extra observations, but both variables are insignificant in one of the regressions. The changes make the dollar differentials change significantly for murder, rape and auto theft. So in Table 28, five of the seven crime categories are classified as disamenities. Removing the three variables for central city status, cost-of-living index and commuting time changes the results more in the wage equation than in the rent equation.

Although the crime figures perform somewhat better for this change, I recommend utilizing all relevant variables possible. Some urban areas, which may be relatively small, are eliminated with the variables' use. However I believe that they are important determinants of wages and rents. The hedonic method is sometimes criticized for its susceptibility to omitted variables, so I believe purposely deleting theoretically relevant variables here has more costs than benefits. Eliminating these variables and adding the extra observations includes one-hundred ten urban areas sampled for both equations, compared to seventy-seven for the rent equation and to ninety-two for the wage equation before this change.

Test for Collinearity

Some researchers may be concerned that collinearity is causing some of the inconsistencies that I have found in the performance of the crime variables. Table 29 gives the pairwise correlation coefficients for the crime variables for the rent and wage equations. The greatest correlation coefficient between the seven individual crime rates is between robbery and auto theft. It is .80 for the rent equation and .78 for the wage equation. The correlation coefficients between the index measures of violent and property crimes are .47 and .42 for the rent and wage equations, respectively. The fiscal factors are the only variables whose correlation coefficients are above .90, and they are only analyzed as separating factors.

These correlations may worry some researchers about collinearity affecting my results. After all, throughout the regressions I have examined, some coefficients do not have the correct theoretical sign, and many variables are not significant, due perhaps to large standard errors that could be caused by multicollinearity. These concerns are warranted, and I have tried several different methods to test for the influence of collinearity on my results. First I will discuss several reasons for why the effect of such a problem may be minimized. The works by Hoehn et al. (1987) and by Clark and Nieves (1994) analyzed these same types of results, and they found no evidence of collinearity significantly degrading their findings, i.e., no insignificant coefficients were linked to the existence of collinearity. With the proper specification, collinearity is not a problem because the estimated coefficients and standard errors are not biased. Not knowing the true specification, the only solution to collinearity is to drop some of the variables involved in the collinear relationship. This process can create biased coefficients due to a specification problem since the crime variables are included for their theoretical relevance. I also have large sample sizes available, which can still give the model power.

An example may help with this explanation. Robbery and auto theft are the most highly correlated crimes in my sample, as seen in Table 29. Therefore individuals and households may respond to them as one unit, although I have not found any research to this effect. If the response to these crimes is not the same, they should be retained separately, even if the supplies are highly correlated. Pindyck and Rubinfeld (1998) find that multicollinearity may be a problem if several variables have high standard errors, and if dropping one or more of these variables from the equation lowers the standard errors of the remaining variables. Although not shown here, I ran the rent and wage regressions, including all crimes, of Tables 21-24 without robbery and then without auto theft. None of the standard errors of the crime variables were affected with these deletions. For all of these new regressions, no variables other than those for the crime rates change significantly in coefficient or significance level.

For the rent regressions run with all crimes other than robbery, the coefficients and significance of the remaining crime variables did change somewhat from the previous regressions with robbery included. In the semi-log regression, murder becomes significant. Another difference is the size of the coefficient of the auto theft variable. In the new log-linear regression, it becomes smaller by a factor of two; it decreases by a factor of ten in the semi-log regression. The significance of the coefficients does not change in either model, as far as going from being significant to insignificant, or vice versa. The coefficients of the other crime variables do not change much in size, except for that of murder, which is now twice as large in the new semi-log regression. The change in the wage regression for the semi-log model without robbery is very much the same. The size of the coefficients of the auto theft and aggravated assault variables are decreased by half while that for murder is twice as great. In the log-linear wage model, the coefficient for auto theft decreases by a factor of ten, although it is insignificant without robbery included. The coefficient for rape becomes significant, and that for aggravated assault becomes insignificant. Both coefficients are similar for these two variables after the change. The coefficient for murder becomes positive, but insignificant.

Running the original regressions of Tables 21-24 without auto theft results in very few changes. For the rent equation, only one noticeable change occurs within the log-linear or semi-log models. The coefficient for robbery decreases by a factor of three in the new log-linear model. The other crime variables are virtually unaffected. Incorporating this change into the semi-log wage regression affects the other crime variables very little. In the log-linear wage model, the size of the coefficient for robbery is halved, while that for murder is increased in absolute value by a factor of five. No significance levels or other coefficients are affected.

Evaluating these regressions with these changes illustrates a potential problem with collinearity, but I believe that all of the crime variables should still be included. The two crimes of robbery and auto theft may be correlated, although their exclusion failed the test of lowering the standard errors of the remaining crime variables. The exclusions do affect the other crime measures somewhat, but affect the other independent variables minimally. These changes in coefficients and significance levels have occurred throughout the analysis when I have examined the use of other alternative models and variables. I do not assume a theory that espouses the effect of robbery on wages or housing prices, but purports that auto theft has no effect, or vice versa. Therefore I continue this analysis with all individual crimes included.

Wage Equation with Renters

As discussed above, I use only renters in the housing equation. I include both renters and homeowners in the wage equations in order to keep the sample as large and representative as possible. However, since homeowners are excluded from the housing equation, it is possible that the average compensating wage differential estimated using both renters and homeowners will be different from that of renters only. Since I ultimately combine the wage and housing effects, this might result in a biased estimate of willingness to pay for crime reductions. To verify that none of my results are driven by this decision, I ran the major wage regressions with only renters included. This new sample has approximately 23,000 observations, but includes the same urban areas. None of the basic determinants change dramatically in coefficient size or significance level for any of the regressions.

The most noticeable change is that some variables become insignificant. For the log-linear regressions, I look at the equivalent of Tables 13 and 22 for the wage equation with index crimes and the individual crimes included, respectively, with each using regional dummy variables. Comparison to Table 13 with index crimes included reveals that two additional non-crime variables have become insignificant and that the violent crime index is now correctly classified as a disamenity, although insignificantly. Comparison to Table 22 with all crimes included shows that nine variables have lost significance, including three crime variables.

The semi-log regressions show a similar pattern. Using only renters with index crimes makes four additional variables insignificant, although the crime variables are unaffected. Comparison with Table 24 with the individual crimes included shows five new insignificant variables, with robbery being the only crime variable affected. The coefficient sign of most variables is unaffected in both the log-linear and semi-log regressions, and any such change is accompanied with insignificance of the coefficient. Because the wage decision should be affected little by renter/owner status and because the smaller sample has less explanatory power for some variables, I believe the original results should be the ones examined.

Variable Measurement Error

I also examine another major change to the regressions described above. For each urban area, Clark and Nieves (1994) used percentages for the manufacturing, unemployment and vacancy variables that were calculated at the regional level, so I initially used this same choice. Hoehn et al. (1987) did not use this set of separating factors. Since I am using regional dummy variables in the regressions, I believe I should also test the model specifications using percentages for the manufacturing, unemployment and vacancy variables that are calculated at the metropolitan area. The results do change somewhat. I examine the log-linear and semi-log models for the major rent and wage equations including index crimes and then all individual crimes, with each using regional dummy variables. For all regressions, the basic determinants are essentially unchanged in size of coefficient and significance level.

I will first examine the variables other than those for the crimes and for the basic determinants. For the rent equations, the major change that occurs is for the Unemployment variable. When measured with the original regional percentage, this variable was always incorrectly signed positively in all rent regressions. I would expect lower rents as incentives to live within areas with higher unemployment rates. I significantly find this effect in all four major rent regressions after the variable is measured for each individual metropolitan area. The other variables for manufacturing and vacancy percentages do not change substantially with this change in any rent regressions. Other non-crime variables within the regressions change little, perhaps gaining or losing significance at the five percent level for one variable per regression.

The results for the wage regressions are somewhat more varied. Once again the Unemployment variable unequivocally performs better. Before the change, the coefficient for this variable is always incorrectly signed positively. Higher unemployment rates should bring about lower wages. When measured for each urban area, this variable is significantly signed negatively. The effect on the Manufacturing variable is mixed with this change. I would expect a greater employment within this industry to increase wages, in part due to the effect of unions. This effect is already found in the original wage regressions, although insignificantly. After the change in measurement techniques, the Manufacturing variable is incorrectly signed in the log-linear models and correctly signed in the semi-log models. The effects on the other non-crime variables are mixed, again perhaps one per regression.

To show the effect on the crime variables, I create Tables 32 and 33 to give the total dollar costs per household when using the percentages for the individual metropolitan areas for the Manufacturing, Unemployment and Vacancy variables. Table 32 gives the results for the log-linear regressions. Incorporating the index crime measures yields somewhat different results from Table 30. When using the regional dummy variables, both index crime variables become negative and insignificant in the housing component when they were correctly and significantly signed before this change. Yet the total effect for the violent crime index is now of the correct sign. Large changes occur for the property crime index when using metropolitan area dummy variables. Both the rent and wage regressions yield large dollar values for this index of opposite sign of those found in Table 30.

Incorporating individual crimes with these variable changes shows a much more similar picture as that found in Table 30. In the section entitled "All crimes" in the bottom portion of Table 32, I show that the sign of the total effect for each crime variable is the same as that found in Table 30, except for murder which now has the correctly signed positive cost to households. The individual dollar amounts are quite similar for all crimes in the total effect. The same variables are significantly classified within the tables, except that rape is now also significantly classified correctly in the rent equation.

Table 33 gives the total costs of crimes from the semi-log regressions, when using the new measurements for the Manufacturing, Vacancy and Unemployment variables. In this case, the dollar amounts for the total effects for the index crime measures are quite similar in comparison to Table 31, except for the property crime variable in the model using metropolitan dummy variables. It has become decidedly positive with the changes shown in Table 33 as both equations are correctly signed now. The total dollar amounts are comparable when incorporating all crimes into the regression. Only murder has changed its sign for the total effect, even though its components from the rent and wage equations have changed little from Table 31.

Within this text I have explored many alternative specifications for the regressions I am studying to verify that the results I find are not being driven by any particular set of questionable variables or models. Before this point, I have not shown new total crime costs, as I do here with Tables 32 and 33, with any of these other specifications. I would simply note any changes in the coefficient sign or significance of the individual variables. Many of these other changes I have incorporated are to verify the basics of the theory or experience of other researchers. I use the economic labor literature to study the wage equation, incorporate a separate dummy variable for New York City to test rent control, etc....

Of the specifications I have tested, I believe this current change in the measurement of specific variables best illustrates the important point that it may be prudent to bound any cost estimates that are found. I originally use the regional specification for these three variables delineated by Clark and Nieves (1994), although they did not explain any theory behind this decision. I altered these variables because I wanted to measure them at the metropolitan area since I was already including regional dummy variables. This change in variable measurement technique does affect other variables within the regressions, especially the crime variables. Although the resulting total effects on crime here are similar to those found in the original specification, it can be seen that the cost estimates will change based upon the models and variables chosen for the regressions.

Regressions using Changes in Crime Rates

One could argue that individuals and households are not as concerned with the levels of the per capita crime rates as they are troubled by the percentage increase in these crimes. The regressions for the rent and wage equations I have used examine data for respondents from the 1980 and 1990 Census. Although not shown here, I also examined the changes in crime that the individuals in these time periods would experience in making their housing and wage decisions. I created variables that represent the percentage changes in the crime rates over the previous three years, from 1977-80 and from 1987-90.

Some of these correlation coefficients were greater than with the absolute levels of crimes. The greatest correlation occurred between the percentage changes in burglary and larceny, being .94 for the wage equation and .97 for the rent equation. Other crimes exhibited very low correlations with their percentage changes. This trend shows that some crimes increase or decrease very much in line with each other while others are very loosely related. In an attempt to counteract any high correlations, I included the levels of the index crime measures in the regressions. The correlations between these gross levels and the individual percentage changes were very low, and positive versus negative in some cases.

I examined both a log-linear and semi-log model, and measured the Unemployment, Manufacturing and Vacancy variables at levels for both the region and for the metropolitan area, for the inclusion of these new variables measuring crimes. The coefficients of some of the non-crime variables were affected, but these changes were almost always accompanied with insignificance of the coefficient. By combining the results from the rent and wage equations, I had four new sets of results to consider. In all four cases, the violent crime index variable was labeled a disamenity while the property crime index was always incorrectly classified as an amenity. This result was the same as when only the index measures were previously used.

For the percentage change crime variables which were added to the analysis, rape, aggravated assault and burglary were labeled as disamenities in all four regressions when the rent and wage components were summed. Larceny and auto theft were labeled as disamenities in some of the regressions and amenities in others. As with the previous analyses in this research, each of the crime variables was almost always signed incorrectly in either the wage or rent equation. This test again shows that the results may be sensitive to the particular variables used to measure the crime effects.

Income Effects

Throughout this study, I have examined the impact of crime and other (dis)amenities on the marginal worker or household in the United States. An obvious question arises as to the effect of crime on different groups within the sample, specifically those within separate income categories. Levitt (1999) studied the changing victimization of the relatively rich and poor between the mid-1970s and the mid-1990s, during which time period income inequality was growing. Using data from the National Crime Victimization Survey (NCVS), he showed that the poor were more likely to be victims of violent crimes at any time in his study. He also found that property crime victimization became increasingly concentrated on the poor over this time period, possibly because the rich could more easily invest in security measures to protect themselves from such crimes. However the rich were not as successful in systematically reducing their rate of victimization compared to the poor in terms of violent crimes. With this information on victimization rates, I hypothesized that I would find a larger impact on the wages and housing costs of the relatively poor for all crimes, but especially so for violent crimes.

To test this hypothesis, I first split the sample into two categories for high and low income. For the housing equation sample, I use a cut-off point of a median family income of $21,000 in 1990 dollars. Running a log-linear regression with all crime rates included yields the Chow test statistic $F(47, 21737) = 50.4$ when comparing the regression results of each income category with the complete sample. The semi-log regression with all crime rates included yields the Chow test statistic $F(47, 21778) = 52.3$. The Chow tests for the same regressions, but replacing the individual crime variables with the index measures, yield very similar results. Because these test statistics are significant, we can reject the hypothesis that the coefficient vectors are the same for the two income categories for the rent equation.

I also check the effect of income on the wage equation. For this sample, I use a cut-off point for high versus low income for an individual of $21,500 in 1990 dollars, which is the median annual income for my sample. The log-linear regression with all crime rates included yields the Chow test statistic F(61, 70221) = 581.6. The equivalent semi-log regression yields the Chow test statistic F(62, 73121) = 555.6. These results show that we can also reject the hypothesis that the two income categories yield the same regression results for the wage equation.

To test both the effects of income and of the crime variables simultaneously, I create dummy variables for the quartiles for the housing and wage equation samples based upon family and individual income, respectively. Then I create interaction terms for the individual crime rates and the quartile dummy variables. I include these interaction terms with the individual crime rates in the log-linear regressions for the housing and wage equations. I then test whether the coefficients of the seven interaction terms for each quartile, based upon the seven specific crime rates, are jointly equal to zero, i.e., whether together they do not have a significant impact upon the dependent variables. I can reject these hypotheses for all income quartiles for both the housing and wage equations, except for the third income quartile in the housing regression. This rejection implies that the crime variables, taken together as a unit, will have an impact on the wages and housing prices of these different groups of individuals.

Next I show the impacts of the individual crime variables on the households and individuals of the top and bottom income quartiles. Table 34 gives the impact of all variables, besides the basic determinants, on the gross rent of the bottom and top quartiles of households based upon family income in 1990 dollars. These figures are comparable to Table 21, which gives the same log-linear results for the rent equation using regional dummy variables for the full sample. Although not shown, the basic determinants of the rent equation for both groups within Table 34 yield essentially the same coefficient sign and significance level as those found throughout this study.

As when discussing the differences in the results for the wage regressions between men and women, some of the new variable coefficients for the different income groups bound the general results of Table 21. For example, the COLI coefficient is 0.269 for the bottom quartile and 0.767 for the top quartile. Approximately in the middle is the COLI coefficient of 0.475 for the full sample of Table 21. The variables for unemployment, vacancy rate, cooling degree-days, precipitation, humidity and intergovernmental revenue also seem to follow this pattern. The variables for manufacturing employment, coastline, population density, Superfund sites, heating degree-days, windspeed, sunshine, commute time and local taxes generally have coefficients for both income groups similar to those found for the full sample. The bottom quartile yields similar coefficient values as the full sample for the Central city and TSP variables, but the top quartile has coefficients that are of the opposite sign, although both are insignificant. Both quartiles have the opposite coefficient sign for the variable for property taxes, although both are insignificant. The top quartile has a much lower coefficient value for T-P ratio than the full sample does, but it is also insignificant.

For the crime variables, the results do vary between the two income groups in Table 34. The coefficient signs are the same for all of these variables for the two groups as for the full sample, except for murder for the bottom quartile and for rape for the top quartile. Both have become correctly classified as disamenities, although insignificantly. The crimes of rape and larceny for the bottom quartile and of robbery for the top quartile have also become insignificant compared to the results for the full sample. Of the correctly signed coefficients, the bottom quartile has a coefficient value more than three times the size of that for the top quartile for aggravated assault and almost twice as great for auto theft. The top quartile is affected more by burglary, to the degree of approximately fifty percent. These results are probably not due to changes in sample selection. Of the seventy-six urban areas sampled for the full sample for the rent equation, the bottom quartile uses all of them, and the top quartile uses only one less. In terms of housing costs, I do find a stronger effect of crimes on the relatively poor, commiserate with my hypothesis, except for burglary. This finding may reflect the fact that I am using data for renters only. This subset of the rich may be less able to engage in preventative measures, as opposed to homeowners, so a crime such as burglary may affect the rich more in my sample.

Table 35 gives the equivalent wage equation results for the bottom and top quartiles in personal income compared to the full log-linear sample in Table 22. Few variables exhibit the bounding trait of coefficient values between the two income groups, as seen with the rent results. The variables for COLI, unemployment rate, population density, cooling degree-days, windspeed, sunshine and all three fiscal factors have nearly the same coefficient value for both groups as found in the full sample. Of the remaining non-crime variables, the coefficient sign has changed from a positive value for the full sample to a negative value for the bottom quartile for the variables for manufacturing employment, coastline, TSP, precipitation, humidity and T-P ratio. The same has occurred for the top quartile for the variables for heating degree-days, humidity and commute time. All such changes are accompanied with insignificance. The new regressions yield significantly lower coefficient values for both income groups for the Central city and Superfund variables.

Of the two income groups, only the top quartile has any significant results for the crime variables in the wage equation, and it is for burglary, which is signed incorrectly. The variable coefficients have switched sign from those for the full sample for larceny for the bottom quartile and for murder, aggravated assault and auto theft for the top quartile. Again these changes are probably not due to sample selection bias, as the samples for both groups comprise eighty-nine urban areas. The insignificant results may occur in this situation from a reduction in sample size for the regressions run with a single quartile. We may expect to find the stronger results from the rent regressions that I did, even with a similar size reduction, due to self-selection within the sample. The crime rates being used are measured at the level of the metropolitan area, but individuals may be segregated and living in different sectors within that area based upon their income levels. If so, different income categories may be experiencing different crime rates, which may affect their valuations of their housing costs, and not necessarily of their wages. Levitt (1999) noted this trend of segregation as a probable reason for the higher victimization of the poor.

CHAPTER V

CONCLUSIONS

For the purpose of policy analysis, it is beneficial to have estimates of the specific costs involved. For example, Ridker and Henning (1967) studied the effects of differences in air quality on property values decades ago. After much research into this area, the Environmental Protection Agency now uses these estimates for cost-benefit analyses, and many states have enacted environmental costing for utility companies based on such research findings. Cohen et al. (1994) discussed how the application of criminal policy analysis could also benefit from specific cost estimates. To this point, the research used to evaluate the costs of specific crimes has focused on the actual costs incurred by the victim or society for the crimes committed.

The approach of evaluating the importance of (dis)amenities on a nationwide scale allows us to objectively view the individual's preferences over locations due to these (dis)amenities. Hoehn et al. (1987) constructed a dollar value for the disamenity of crime, as measured by the average household. This value was determined in a market system by individuals being compensated through their wages and housing prices for the chance of becoming a victim of crime, and suffering the subsequent losses that Cohen (1988) described. If the trade-off is too great, the individuals can change their location and so consumption of housing and other amenities.

The hedonic approach seems to be the most direct route to estimating the cost of crime to individuals, as measured by their own choices. I expand this technique to consider individual crimes. By including additional data, I estimate the value of reducing specific crimes. This last step is important for specific policy analyses. For example a larger police force may reduce overall crime, but other techniques such as tougher sentencing for specific offenses affect crime in a different way. All crime prevention techniques have price tags, but government agencies and individual communities may be able to use such value estimates of specific crimes to determine which programs pass a cost-benefit test.

The results are not as conclusive as I would have liked since the effects of the crimes vary between regressions. This fact can be seen in Table 36, which shows the sign and significance of the crime variables in the regressions run in this research. A "Y" indicates that the result is correctly classified as a disamenity, whether it is in the housing or wage components or in the total effect. A "N" indicates that the result is incorrectly signed. According to the formula for the evaluation of the marginal amenity price, $f_r = k_r dq_r/ds - dw/ds$, the crime variables, as disamenities, should have a negative total effect. By the hedonic theory, the effect of these crimes would be negative on the housing component and positive on the wage component. Table 36 shows that the effects on the two components, and on the total effect, depends upon the functional form and the particular variables used in the regression. All of these results are from regressions run with regional dummy variables.

The first set of columns of Table 36 gives the results for the crime variables for the log-linear regressions of Tables 12, 13, 21 and 22. The regressions with the index crimes do not perform well. The wage component has the incorrect sign for both crime variables and dominates the total effect. I do not include the significance of the total effect because I would have to assume that no covariance exists between the housing and wage coefficients, which I explained earlier in the text. The second set of columns gives the results for the semi-log regressions. The index measure for violent crime now has the correct total effect. The total effects for the individual crime variables are the same as those for the log-linear regressions, except for murder, which is now correctly signed. The last two sets of columns give the results for the same regressions of the first two sets of columns, except that the variables for the manufacturing, unemployment and vacancy percentages are measured for each urban area, rather than at the regional level. What is less convincing for this research is the number of changes that occur between the housing and wage components when the functional form is changed or when the variables are measured differently. The results must also be considered in the light that many of the coefficients of the housing and wage regressions are significantly labeled incorrectly.

One might expect this result. We do not know the true functional form of the wage and housing price equations. My intent is to estimate various specifications, as many other researchers have done in the past, to test for a robustness of findings to form a reasonable estimate of individual crime effects on households and individuals across the United States. Unfortunately I find that several of the individual crime variables are still incorrectly classified as amenities, even with these changes in the models and in the variables I examine.

As mentioned above, I find that the results for the index crime measures are mixed in terms of violent versus property crimes. The property crime index consistently has a positive total amenity value. Hoehn et al. (1987) and Clark and Nieves (1994) only used an index measure for violent crimes, so I do not know if they would have found the same result as I did with the property crime index variable. This variable's inclusion may be proxying for a supply effect of crime. The dependent variables are measuring housing values and income in the rent and wage equations, respectively. As these measures rise, perhaps property crime is following the same trend. This explanation would probably not work as well for violent crimes, which may explain its better performance in the research. The violent crime index is classified as a disamenity in three of the four models shown in Table 36 when the index measures are used. Of these correct measurements, the cost estimates for a ten-percent increase in violent crime ranges from $17-66 per household annually in 1980-90 dollars. Hoehn et al. found an estimate of $67 for a ten percent change in this variable, and Clark and Nieves found a value of $83, with both measured in 1980 dollars. So my estimates would seem to fall near an acceptable range based upon previous research.

When studying the effects of all seven crime rates in level form, the results for the wage equation dominate the combined results for practically all outcomes, both within the log-linear and semi-log models. In both model formats, rape, robbery and larceny are the only crime variables that are consistently classified as disamenities with positive annual costs to households. Again an argument for collinearity affecting my results can be made here. Perhaps these three crimes are the only ones which residents consider in their wage and housing decisions. However Table 29 shows some strong correlation coefficients between these three crime variables and the remaining four, which are labeled as amenities in my analysis. In particular, robbery is highly correlated with murder, aggravated assault and auto theft in both the rent and wage samples. Burglary is correlated with both rape and larceny. Collinearity may be difficult to prove or disprove, but its impact should be considered in this context.

If these three crime variables do have an impact on households, the cost estimates I have found to decrease the crime rates for the marginal household from their means by ten percent annually range from $4-42 for rape, $51-93 for robbery and $29-296 for larceny, based upon Tables 30-33. These findings hold true whether the Manufacturing, Unemployment and Vacancy variables are measured at the regional or SMSA level. However all effects are determined by the relative size of the rent and wage effects, as the two are of the opposite sign in all cases, except for murder in the log-linear model. This phenomenon seems to justify the use of both equations in determining the effect of (dis)amenities. If I use only the rent equation, my findings will be reversed. These ranges of dollar estimates also show the importance of the particular functional form and variables chosen for the estimation.

Using these cost estimates, I can calculate a cost per individual crime. From Tables 1 and 3, I find that the population size of the average metropolitan area experienced by the individuals and households in my sample is 3,473,175; this number is an average between the housing and wage samples which have different population means individually. Using the mean rate for rape of 46.5 crimes per 100,000 capita committed annually between my housing and wage samples, I calculate that the "average" rape costs a household $6875 - $72,192 in 1980-90 dollars based upon each household in this area being willing to pay $4-42 annually to reduce rapes by ten percent. This estimate uses an average number of households per metropolitan area to be 1,291,143 calculated from a mean number of 2.69 people per household in the United States during this time period, according to the US Census Bureau. Similarly I can use the other cost figures above to find that a robbery costs \$2239 - \$4094 at a mean rate of 291 crimes per 100,000 committed annually and that a larceny costs \$8-89 if the mean crime rate is 3520 per 100,000 capita as in my sample. If I use the median population figure of 2,266,908 for the metropolitan areas of my sample with the same cost figures, I find that a rape will cost \$7235 - \$76,379, that a robbery will cost \$2969 - \$5409 and that a larceny will cost \$10-97 per household. These figures compare to a cost per individual of \$51,058 for rape, \$12,594 for robbery and \$181 for larceny, in 1985 prices, that Cohen (1990) found. Considering an average of 2.69 people per household, my range of cost estimates will be somewhat smaller than what he found for these crimes, but not out of the range for comparison.

Hopefully policy analysts can expand the research on these crime cost figures. Perhaps in the future, more detailed information may become available to better study the effects of individual crimes on a nationwide scale. I believe that significant hurdles may exist at this time in terms of obtaining data for such a task that does not involve problems with collinearity or specification. One possible later extension for other researchers or myself would be to use these kinds of estimates to study migration into and out of specific urban areas. My current study assumes migrants have no real effect on the equilibrium housing and wage prices found. Berger and Blomquist (1992) used their hedonic approach to study this topic, incorporating changes in location-specific amenities with previously used disequilibrium wage gains. It may be interesting to study migration with a discrete choice model used by other researchers after measuring drastic changes in crimes within metropolitan areas, coupled with the type of cost figures I have derived.

APPENDIX A

TABLES

Table 1
DESCRIPTIVE STATISTICS FOR TOTAL SAMPLE FOR RENT EQUATION

VARIABLE	OBS	MIN	MAX*	MEAN	STD DEV	MEDIAN
Year	21872	1980	1990	1984.30	0.50	1980
Gross rent**	21872	50.00	1878.00	505.60	241.10	464.40
Condo	21872	0.00	1.00	0.04	0.19	0.00
Kitchen	21872	0.00	1.00	0.99	0.09	1.00
Other rooms	21872	1.00	9.00	4.18	1.43	4.00
Plumbing	21872	0.00	1.00	1.00	0.07	1.00
Building age	21872	1.00	55.00	25.61	15.98	25.00
Units in structure	21872	1.00	10.00	6.40	2.51	6.00
Water	21872	0.00	1.00	0.98	0.15	1.00
Sewage	21872	0.00	1.00	0.95	0.21	1.00
Bedrooms	21872	1.00	6.00	2.85	0.90	3.00
Detached	21872	0.00	1.00	0.19	0.39	0.00
Acreage	21872	0.00	1.00	0.96	0.20	1.00
Time in residence	21872	1.00	35.00	4.85	6.44	3.00
Central city	21872	0.00	1.00	0.58	0.49	1.00
COLI	21872	71.85	102.62	85.20	9.07	81.84
Manufacturing - R	21872	11.60	28.80	20.13	4.71	19.60
Unemployed - R	21872	5.00	12.50	8.42	1.88	7.80
Vacancy - R	21872	5.60	14.20	8.26	2.46	7.50
Manufacturing - S	21872	3.60	38.29	18.45	6.04	18.96
Unemployed - S	21872	3.39	11.66	6.37	1.60	6.68
Vacancy - S	21872	4.49	15.18	6.97	2.31	6.22
Coastline	21872	0.00	1.00	0.56	0.50	1.00
Population	21872	230464	9570256	3808136	3405364	2357192
Superfund	21872	1.00	436.00	80.01	72.56	54.00
Heating days	21872	200.00	10570.00	4190.96	1922.29	4791.00
Cooling days	21872	0.00	4198.00	1292.02	785.29	1037.00
Precipitation	21872	4.13	57.18	34.25	12.62	38.58
Windspeed	21872	6.30	12.70	9.24	1.62	9.20
Sunshine	21872	43.00	86.00	61.03	8.33	59.00
Humidity	21872	20.00	64.00	55.74	7.23	56.00
Pop density	21872	35.38	6108.71	1661.28	2140.75	559.67
Intergov rev***	21872	162.08	2212.36	835.43	691.14	529.06
Local taxes***	21872	84.77	2088.12	819.87	638.48	620.04
Property taxes***	21872	76.13	1194.95	535.47	346.44	377.61
TSP	21872	38.34	118.44	63.45	16.18	57.03
T-P ratio	21872	0.05	0.11	0.07	0.01	0.07
Murder	21872	1.54	27.10	13.30	6.37	13.49
Rape	21872	12.27	99.62	45.88	13.51	42.96

Table 1, continued

Robbery	21872	25.86	1073.61	270.33	194.81	234.26
Agg assault	21872	64.65	1130.68	435.20	214.25	386.60
Burglary	21872	529.02	2928.12	1807.49	572.50	1840.96
Larceny	21872	1520.24	6269.62	3508.14	824.09	3340.36
Auto theft	21872	151.51	1882.21	657.28	444.30	568.31
Violent crimes	21872	106.42	2291.74	764.71	375.51	613.47
Property crimes	21872	2861.38	11079.95	5972.90	1245.47	6116.09
Commute time	21872	15.10	45.90	25.31	6.06	22.80
% chg murder	21018	-46.93	272.52	16.02	30.60	20.54
% chg rape	21018	-45.38	274.62	12.28	24.56	5.29
% chg robbery	21018	-93.32	138.47	-0.04	52.59	12.73
% chg agg assault	21018	-30.66	167.56	19.25	20.16	20.90
% chg burglary	21018	-45.94	42.73	4.84	19.47	4.17
% chg larceny	21018	-26.35	41.22	7.25	12.55	7.10
% chg auto theft	21018	-85.71	104.10	-3.17	45.84	6.68

* Variables with 1 for the maximum are dummy variables.

** Expressed in 1990 dollars, including the cost of utilities.

*** Per capita revenue and tax figures are computed for the entire sample and not in equivalent dollar figures here.

Table 2
DESCRIPTIVE STATISTICS BY YEAR FOR RENT EQUATION

	1980 sample*			1990 sample*		
VARIABLE	MEAN	10% q**	90% q**	MEAN	10% q**	90% q**
Gross rent***	453.21	230.48	708.64	573.75	285.00	933.00
Condo	0.01	0.00	0.00	0.07	0.00	0.00
Kitchen	0.99	1.00	1.00	1.00	1.00	1.00
Other rooms	4.12	3.00	6.00	4.25	3.00	6.00
Plumbing	0.99	1.00	1.00	1.00	1.00	1.00
Building age	27.10	8.00	45.00	23.68	3.50	55.00
Units in structure	6.41	3.00	10.00	6.38	3.00	10.00
Water	0.98	1.00	1.00	0.97	1.00	1.00
Sewage	0.96	1.00	1.00	0.95	1.00	1.00
Bedrooms	2.81	2.00	4.00	2.90	2.00	4.00
Detached	0.17	0.00	1.00	0.22	0.00	1.00
Acreage	0.95	1.00	1.00	0.97	1.00	1.00
Time in residence	5.32	1.00	15.00	4.24	1.00	15.00
Central city	0.68	0.00	1.00	0.45	0.00	1.00
COLI	87.38	76.99	102.62	82.35	77.70	86.14
Manufacturing - R	22.84	17.80	28.80	16.60	14.80	19.85
Unemployed - R	9.71	7.80	12.50	6.74	6.00	7.10
Vacancy - R	6.89	5.70	9.40	10.04	7.50	13.20
Manufacturing - S	20.69	15.53	31.08	15.53	7.42	20.49
Unemployed - S	6.71	4.26	8.95	5.94	4.15	7.37
Vacancy - S	6.31	4.83	8.57	7.82	5.49	11.64
Coastline	0.58	0.00	1.00	0.54	0.00	1.00
Population	4091818	533152	9570256	3439173	787408	8884224
Superfund	54.26	17.00	118.00	113.50	36.00	164.00
Heating days	4695.43	1606.00	6563.00	3534.84	1256.00	6497.00
Cooling days	1181.02	531.00	2043.00	1436.39	507.00	2700.00
Precipitation	36.68	15.31	44.76	31.08	13.39	46.07
Windspeed	9.70	7.20	11.27	8.64	6.85	10.80
Sunshine	60.35	54.00	68.00	61.91	49.00	73.00
Humidity	55.62	53.00	61.00	55.91	52.00	62.00
Pop density	2270.91	221.17	6108.71	868.39	269.42	2188.25
Intergov rev****	941.91	240.80	2212.36	696.94	340.35	1135.43
Local taxes****	889.55	228.64	2088.12	729.23	501.38	956.22
Property taxes****	559.41	159.56	1194.95	504.32	346.34	725.94
TSP	64.61	51.91	82.39	61.95	49.34	93.41
T-P ratio	0.06	0.06	0.07	0.07	0.06	0.09
Murder	14.04	5.85	20.32	12.34	3.29	19.90
Rape	43.03	30.82	55.46	49.58	30.54	69.58

Table 2, continued

Robbery	195.26	52.76	408.11	367.96	127.24	710.18
Agg assault	367.29	189.62	496.95	523.54	236.12	976.19
Burglary	2114.01	1420.75	2619.19	1408.82	875.56	1966.58
Larceny	3494.88	2755.30	4186.48	3525.38	2234.15	5380.91
Auto theft	421.34	156.54	729.47	964.13	311.40	1557.61
Violent crimes	619.63	400.51	857.34	953.42	443.63	1753.67
Property crimes	6030.23	4783.35	6702.90	5898.33	3809.48	8292.91
Commute time	25.55	18.80	35.00	25.01	20.10	29.90
% chg murder	15.25	-12.38	31.58	16.96	-27.39	46.86
% chg rape	13.74	-0.79	40.88	10.52	-14.22	35.47
% chg robbery	-14.35	-93.32	51.45	17.29	-22.16	37.05
% chg agg assault	14.79	1.79	42.40	24.64	7.34	60.72
% chg burglary	16.89	0.03	29.62	-9.76	-30.01	4.17
% chg larceny	11.67	-2.34	19.09	1.90	-9.78	14.27
% chg auto theft	-25.73	-85.71	21.31	24.16	-1.73	67.44

* The samples include 12,365 and 9,507 observations, respectively, for 1980 and 1990.

** The last 2 columns for each sample represent the 10% and 90% quartile figures.

*** Expressed in 1990 dollars, including the cost of utilities.

**** The tax and revenue figures are not in equivalent dollar terms between the 2 samples.

Table 3
DESCRIPTIVE STATISTICS FOR TOTAL SAMPLE FOR WAGE EQUATION

VARIABLE	OBS	MIN	MAX*	MEAN	STD DEV	MEDIAN
Year	73245	1980	1990	1986.50	0.48	1990
Hourly wage**	73245	2.50	300.00	13.68	12.21	10.96
No. of children	73245	0.00	9.00	0.92	1.16	0.00
Age	73245	16.00	90.00	37.08	12.26	35.00
Sex	73245	0.00	1.00	0.45	0.50	0.00
Marital status	73245	0.00	1.00	0.65	0.48	1.00
Speak English	73245	0.00	1.00	0.98	0.15	1.00
In school	73245	0.00	1.00	0.11	0.31	0.00
Years of education	73245	0.00	16.00	13.24	2.54	14.00
Veteran status	73245	0.00	1.00	0.19	0.39	0.00
Commute time	73245	0.00	99.00	23.56	16.57	20.00
Annual hours	73245	3.00	5148.00	1912.73	682.24	2080.00
Central city	73245	0.00	1.00	0.53	0.50	1.00
White	73245	0.00	1.00	0.87	0.33	1.00
Black	73245	0.00	1.00	0.09	0.29	0.00
Full-time	73245	0.00	1.00	0.78	0.42	1.00
Experience	73245	0.00	77.50	17.85	12.59	16.00
Self-employed	73245	0.00	1.00	0.04	0.21	0.00
COLI	73245	71.85	102.62	82.20	6.04	80.58
Manufacturing - R	73245	11.60	28.80	18.76	4.41	16.50
Unemployed - R	73245	5.00	12.50	7.79	1.81	7.10
Manufacturing - S	73245	3.60	39.91	17.65	6.33	18.19
Unemployed - S	73245	3.11	11.66	6.06	1.59	5.82
Coastline	73245	0.00	1.00	0.52	0.50	1.00
Population	73245	86596	9570256	3138214	2835378	2176624
Superfund	73245	0.00	436.00	87.69	65.66	71.00
Heating days	73245	200.00	10570.00	3980.75	2079.08	4522.00
Cooling days	73245	0.00	4198.00	1350.14	806.54	1132.00
Precipitation	73245	4.13	61.16	33.07	12.82	36.63
Windspeed	73245	6.30	13.70	8.89	1.52	8.70
Sunshine	73245	43.00	86.00	61.17	8.41	59.00
Humidity	73245	20.00	64.00	56.04	6.58	58.00
Pop density	73245	35.38	6108.71	997.62	1301.16	557.35
Intergov rev***	73245	162.08	2212.36	658.78	452.97	526.68
Local taxes***	73245	84.77	2088.12	683.84	422.24	620.04
Property taxes***	73245	38.82	1194.95	471.54	244.95	389.18
TSP	73245	38.34	118.44	63.46	16.79	56.50
T-P ratio	73245	0.05	0.11	0.07	0.01	0.07
Murder	73245	0.57	27.10	12.44	6.45	13.13

Table 3, continued

Rape	73245	11.94	99.62	47.12	15.03	47.40
Robbery	73245	16.50	1073.61	310.79	189.49	271.57
Agg assault	73245	51.19	1130.68	456.82	238.43	386.60
Burglary	73245	529.02	2928.12	1597.66	505.18	1482.72
Larceny	73245	1161.72	6269.62	3531.46	862.42	3390.43
Auto theft	73245	71.60	1882.21	771.67	445.59	687.06
Violent crimes	73245	80.20	2291.74	827.16	412.38	721.70
Property crimes	73245	1773.75	11079.95	5900.79	1325.55	5775.61
Commute time	73245	12.20	45.90	23.87	4.33	22.70
% chg murder	71191	-59.10	1003.20	18.18	55.38	13.27
% chg rape	71211	-45.38	274.62	14.79	29.18	7.15
% chg robbery	71289	-93.32	2841.03	17.32	101.96	20.05
% chg agg assault	71289	-51.36	1177.42	24.74	44.35	24.29
% chg burglary	71289	-45.94	2026.81	0.93	69.95	-2.73
% chg larceny	71289	-26.35	5385.89	10.90	178.43	5.17
% chg auto theft	71289	-85.71	2781.01	15.91	97.81	14.06

* Variables with 1 for the maximum are dummy variables.

** Expressed in 1990 dollars.

*** Per capita revenue and tax figures are computed for the entire sample and not in equivalent dollar figures here.

Table 4
DESCRIPTIVE STATISTICS BY YEAR FOR WAGE EQUATION

	1980 sample*			1990 sample*		
VARIABLE	MEAN	10%**	90%**	MEAN	10%**	90%**
Hourly wage***	13.54	5.21	22.97	13.75	4.93	23.86
No. of children	1.01	0.00	3.00	0.88	0.00	2.00
Age	36.70	21.00	56.00	37.29	23.00	54.00
Sex	0.43	0.00	1.00	0.46	0.00	1.00
Marital status	0.68	0.00	1.00	0.63	0.00	1.00
Speak English	0.99	1.00	1.00	0.97	1.00	1.00
In school	0.09	0.00	0.00	0.12	0.00	1.00
Years of education	12.75	10.00	16.00	13.50	11.00	16.00
Veteran status	0.22	0.00	1.00	0.17	0.00	1.00
Commute time	22.88	5.00	45.00	23.92	5.00	45.00
Annual hours	1849.38	780.00	2496.00	1946.25	940.00	2600.00
White	0.89	0.00	1.00	0.86	0.00	1.00
Black	0.09	0.00	0.00	0.09	0.00	0.00
Full-time	0.75	0.00	1.00	0.79	0.00	1.00
Experience	17.96	2.00	38.00	17.80	3.00	35.00
Self-employed	0.04	0.00	0.00	0.05	0.00	0.00
Central city	0.59	0.00	1.00	0.51	0.00	1.00
COLI	83.23	76.05	102.62	81.66	77.70	85.03
Manufacturing - R	22.48	17.80	28.80	16.79	14.80	19.85
Unemployed - R	9.77	7.50	12.50	6.74	6.40	7.10
Manufacturing - S	21.28	14.07	31.52	15.72	8.29	20.49
Unemployed - S	6.57	4.17	9.04	5.78	4.15	7.37
Coastline	0.46	0.00	1.00	0.56	0.00	1.00
Population	2635488	383948	9570256	3404277	787408	8884224
Superfund	53.57	10.00	125.00	105.75	38.00	164.00
Heating days	4654.76	1549.00	6563.00	3624.03	1306.00	6747.00
Cooling days	1271.45	506.00	2761.00	1391.79	507.00	2700.00
Precipitation	35.38	15.31	45.22	31.85	13.39	46.07
Windspeed	9.35	7.10	11.27	8.64	6.85	10.80
Sunshine	60.70	54.00	70.00	61.41	49.00	73.00
Humidity	55.23	44.00	61.00	56.47	52.00	62.00
Pop density	1263.13	165.09	6108.71	857.11	276.40	2188.25
Intergov rev****	604.95	206.00	2212.36	687.27	322.37	1135.43
Local taxes****	572.75	199.88	2088.12	742.63	484.88	964.95
Property taxes****	390.48	154.29	1194.95	514.44	364.31	725.94
TSP	67.24	51.91	83.73	61.45	48.43	93.41
T-P ratio	0.06	0.06	0.07	0.08	0.06	0.09
Murder	12.38	4.34	20.32	12.47	3.29	19.90

Table 4, continued

Rape	42.49	23.43	60.65	49.57	30.54	69.58
Robbery	220.91	52.76	408.11	358.35	123.72	710.18
Agg assault	330.28	182.37	496.95	523.79	233.77	976.19
Burglary	1959.91	1383.30	2619.19	1405.95	891.58	2164.20
Larceny	3512.49	2710.18	4213.27	3541.50	2683.00	5380.91
Auto theft	478.02	156.54	964.45	927.08	293.97	1557.61
Violent crimes	606.06	368.31	857.34	944.18	443.63	1753.67
Property crimes	5950.41	4668.30	6857.13	5874.53	3809.48	8292.91
Commute time	22.98	18.40	35.00	24.34	20.10	28.70
% chg murder	19.26	-16.96	43.53	17.65	-27.39	46.86
% chg rape	18.37	-0.79	45.11	13.04	-5.20	52.23
% chg robbery	16.15	-93.32	52.90	17.89	-22.16	68.59
% chg agg assault	22.09	-2.26	43.41	26.04	6.18	60.72
% chg burglary	22.22	-2.48	33.71	-9.47	-30.01	23.93
% chg larceny	28.74	-3.68	22.63	2.19	-14.79	20.43
% chg auto theft	1.83	-85.71	25.09	22.78	-1.73	67.44

* The samples include 25,349 and 47,897 observations, respectively, for 1980 and 1990.

** The last 2 columns for each sample represent the 10% and 90% quartile figures.

*** Expressed in 1990 dollars.

**** The tax and revenue figures are not in equivalent dollar terms between the 2 samples.

Table 5
PERCENTAGE OF OBSERVATIONS FOR INDIVIDUALS BY OCCUPATION/INDUSTRY

		1980		1990	
OCCUPATION	Total	Male	Female	Male	Female
Managerial & professional	30.9%	28.3%	24.8%	32.3%	34.1%
Technical, sales & administrative support	34.0%	20.5%	50.5%	24.0%	46.5%
Service	10.2%	9.1%	13.3%	8.6%	11.5%
Precision production, craft & repair	11.1%	20.3%	2.2%	17.2%	2.1%
Operators & laborers	13.0%	21.0%	9.1%	16.4%	5.6%
Farming, forestry & fishing*	0.8%	0.9%	0.2%	1.5%	0.3%
INDUSTRY					
Agriculture, forestries & fisheries	0.8%	0.7%	0.3%	1.3%	0.6%
Mining	0.7%	1.2%	0.5%	0.7%	0.5%
Construction	5.5%	8.0%	1.0%	9.3%	1.5%
Transportation, communications & utilities	7.9%	10.5%	4.8%	9.8%	5.6%
Wholesale & retail trade	19.9%	19.2%	20.8%	20.5%	19.0%
Finance, insurance & real estate	8.4%	5.8%	10.7%	6.0%	11.7%
Business & repair services	4.9%	4.7%	3.6%	6.0%	4.4%
Personal services	2.2%	1.3%	3.1%	1.6%	3.2%
Entertainment & recreation	1.3%	0.9%	0.9%	1.6%	1.4%
Professional services	22.9%	12.7%	33.0%	14.1%	35.0%
Public administration	6.2%	7.1%	6.1%	6.2%	5.9%
Manufacturing*	19.3%	28.0%	15.4%	22.9%	11.3%
Observations	73,245	14,389	10,960	26,070	21,827

* These categories are not represented as dummy variables to avoid perfect collinearity within the regressions.

Table 6
PERCENTAGE OF OBSERVATIONS BY METROPOLITAN AREA

METROPOLITAN AREA	STATE	WAGE EQ 1980	WAGE EQ 1990	RENT EQ 1980	RENT EQ 1990
Abilene*	TX	0.26%	NA**	NA	NA
Albany-Schenectady-Troy	NY	1.50%	1.73%	1.33%	1.21%
Albuquerque	NM	0.73%	NA	0.50%	NA
Amarillo	TX	0.30%	NA	NA	NA
Anchorage	AK	NA	0.31%	NA	0.43%
Atlanta	GA	NA	4.24%	NA	3.60%
Austin	TX	NA	2.11%	NA	1.98%
Baltimore	MD	3.80%	3.80%	3.52%	2.70%
Beaumont/Port Arthur/Orange	TX	0.67%	0.23%	0.53%	0.22%
Billings	MT	0.15%	NA	NA	NA
Binghamton	NY	0.39%	0.20%	0.08%	0.18%
Birmingham	AL	1.21%	0.31%	1.02%	0.36%
Boise City	ID	0.32%	NA	NA	NA
Buffalo/Niagara Falls	NY	1.94%	2.32%	2.47%	1.59%
Charleston	SC	0.50%	0.19%	0.38%	0.29%
Charlotte/Gaston/Rock Hill	NC/SC	1.16%	0.07%	0.69%	NA
Cincinnati/Hamilton	OH/KY/IN	2.77%	0.15%	2.38%	0.13%
Cleveland	OH	NA	3.51%	NA	2.66%
Columbia	MO	0.31%	NA	NA	NA
Columbia	SC	0.62%	0.24%	0.48%	0.04%
Columbus	OH	1.97%	0.32%	2.40%	0.13%
Corpus Christi	TX	0.34%	NA	NA	NA
Dallas/Forth Worth/Arlington	TX	NA	8.70%	NA	7.53%
Dayton/Springfield	OH	1.55%	0.30%	1.14%	0.60%
Denver/Boulder/Longmont	CO	2.78%	3.77%	2.35%	3.07%
Des Moines	IA	NA	0.69%	NA	0.43%
Detroit	MI	7.60%	NA	5.40%	NA
Duluth/Superior	MN/WI	0.44%	NA	0.34%	NA
El Paso	TX	0.54%	NA	0.40%	NA
Evansville	IN/KY	0.40%	NA	0.23%	NA
Fargo/Moorhead	ND/MN	0.19%	NA	NA	NA
Fort Wayne	IN	0.65%	0.65%	0.50%	0.32%
Fresno	CA	0.67%	0.81%	0.74%	1.08%
Grand Rapids	MI	NA	0.54%	NA	0.46%
Green Bay	WI	0.39%	NA	NA	NA
Greensboro/Winston-Salem/Highpoint	NC	1.15%	1.23%	0.87%	0.95%
Greenville/Spartanburg	SC	0.75%	NA	0.55%	NA

Table 6, continued

Harrisburg/Lebanon/Carlisle	PA	0.78%	0.04%	0.23%	0.21%
Hartford/Bristol/Middletown	CT	2.00%	1.64%	1.35%	1.19%
Houston/Brazoria	TX	4.47%	5.60%	3.21%	5.51%
Indianapolis	IN	2.19%	0.58%	1.69%	0.48%
Jackson	MS	0.45%	NA	0.38%	NA
Jacksonville	FL	NA	1.11%	NA	0.16%
Kansas City	MO/KS	1.90%	0.04%	2.07%	0.29%
Knoxville	TN	0.79%	0.27%	0.54%	0.13%
Lansing/East Lansing	MI	0.71%	0.35%	0.40%	0.28%
Las Vegas	NV	NA	0.04%	NA	1.84%
Lincoln	NE	0.43%	NA	NA	NA
Little Rock/North Little Rock	AR	0.48%	0.04%	0.56%	0.04%
Los Angeles/Long Beach	CA	NA	16.67%	NA	16.50%
Louisville	KY/IN	1.64%	1.93%	1.34%	1.06%
Lubbock	TX	0.25%	NA	NA	NA
Lynchburg	VA	0.32%	NA	NA	NA
Madison	WI	0.65%	NA	0.62%	NA
Memphis	TN/AR/MS	NA	1.21%	NA	0.94%
Miami	FL	NA	0.10%	NA	1.79%
Minneapolis/St. Paul	MN	NA	3.90%	NA	3.19%
Montgomery	AL	0.43%	0.42%	NA	0.24%
Nashville	TN	1.22%	0.50%	0.84%	0.70%
New York/Bergen/Passaic/Patterson	NY/NJ	14.24%	NA	31.77%	NA
Norfolk/Virginia Beach/Newport News	VA	1.33%	NA	1.29%	NA
Oklahoma City	OK	1.38%	0.03%	1.14%	0.70%
Omaha	NE/IA	0.96%	0.09%	1.23%	0.14%
Pensacola	FL	0.32%	NA	NA	NA
Peoria	IL	0.71%	NA	0.32%	NA
Philadelphia	PA/NJ	NA	2.03%	NA	5.36%
Phoeniz/Mesa	AZ	2.24%	NA	1.59%	NA
Pittsburgh/Beaver County	PA	NA	0.13%	NA	2.40%
Portland/Vancouver	OR/WA	2.02%	2.67%	2.05%	2.31%
Providence/Fall River/Pawtuckett	RI/MA	1.93%	NA	1.77%	NA
Pueblo	CO	0.06%	NA	NA	NA
Raleigh-Durham	NC	0.88%	0.03%	0.99%	NA
Reno	NV	NA	0.60%	NA	0.84%
Richmond/Petersburg/Colonial Heights	VA	1.49%	0.04%	1.04%	NA
Rochester	NY	1.59%	NA	1.09%	NA
Sacramento	CA	1.55%	2.43%	1.67%	2.43%
St. Louis	MO/IL	4.09%	NA	3.67%	NA
Salt Lake City/Ogden	UT	1.73%	0.35%	1.16%	0.40%
San Antonio	TX	1.74%	NA	1.14%	NA

Table 6, continued

San Diego	CA	2.75%	4.56%	3.78%	5.40%
Seattle/Everett	WA	NA	1.86%	NA	2.91%
Shreveport	LA	0.48%	NA	0.49%	NA
Spokane	WA	NA	0.60%	NA	0.59%
Springfield	IL	0.43%	NA	NA	NA
Syracuse	NY	0.97%	1.38%	0.70%	1.20%
Tampa/St. Petersburg/Clearwater	FL	NA	3.11%	NA	2.97%
Toledo	OH/MI	NA	0.08%	NA	0.59%
Tucson	AZ	1.00%	NA	0.74%	NA
Tulsa	OK	1.11%	NA	0.84%	NA
Washington	MD/VA/WV	NA	8.83%	NA	6.99%
Wichita	KS	NA	0.31%	NA	0.24%
Wilmington	NC	0.27%	NA	NA	NA
Observations		25,349	47,897	12,365	9,507

* No dummy variable exists for Abilene, TX to avoid perfect collinearity within the regressions.

** NA indicates no observations present for that particular metropolitan area

Table 7
PERCENTAGE OF OBSERVATIONS BY REGION

	WAGE EQ			RENT EQ		
	Total	1980	1990	Total	1980	1990
New England	2.4%	3.9%	1.6%	2.3%	3.1%	1.2%
Middle Atlantic	12.5%	21.4%	7.8%	26.6%	37.7%	12.2%
West North Central	2.1%	3.8%	1.1%	2.4%	3.3%	1.1%
South Atlantic	19.4%	12.6%	23.0%	14.0%	9.8%	19.5%
East South Central	2.4%	4.1%	1.5%	2.2%	2.8%	1.4%
West South Central	15.1%	12.0%	16.7%	11.6%	8.3%	16.0%
Mountain	6.2%	9.0%	4.8%	6.3%	6.3%	6.2%
Pacific	22.0%	7.0%	29.9%	18.4%	8.2%	31.7%
East North Central*	10.0%	16.9%	6.3%	9.5%	12.5%	5.5%
Combination**	7.9%	9.4%	7.2%	6.8%	8.0%	5.3%
Observations	73,245	25,349	47,897	21,872	12,365	9,507

* No regional dummy variable exists for the East North Central division to avoid perfect collinearity.

** The combination figures represent the metropolitan areas which span at least two regions.

Table 8
BASIC REGRESSIONS FOR RENT EQUATION
using regional dummy variables

LOG-LINEAR REGRESSION*

Gross Rent	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Bedrooms	0.141	0.0187	7.55	0.105	0.178
Sewage**	0.137	0.0176	7.80	0.103	0.172
Kitchen**	-0.050	0.0371	-1.34	-0.122	0.023
Plumbing**	0.365	0.0597	6.12	0.248	0.482
Detached**	0.164	0.0087	18.83	0.147	0.181
Water**	0.084	0.0266	3.17	0.032	0.136
Building age	-0.105	0.0042	-25.13	-0.113	-0.097
Other rooms	0.302	0.0173	17.51	0.268	0.336
Condo**	0.202	0.0162	12.45	0.170	0.234
Acreage**	-0.017	0.0162	-1.07	-0.049	0.015
Time**	0.691	0.0072	95.75	0.677	0.705
Constant	4.593	0.0709	64.83	4.454	4.732

R-squared: 0.5023

SEMI-LOG REGRESSION*

Gross Rent	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Bedrooms	0.036	0.0069	5.18	0.022	0.049
Sewage**	0.136	0.0173	7.86	0.102	0.170
Kitchen**	-0.026	0.0372	-0.70	-0.099	0.047
Plumbing**	0.357	0.0587	6.09	0.242	0.472
Detached**	0.120	0.0089	13.57	0.103	0.138
Water**	0.077	0.0262	2.96	0.026	0.129
Building age	-0.006	0.0002	-25.41	-0.006	-0.005
Other rooms	0.100	0.0041	24.29	0.092	0.108
Condo**	0.195	0.0160	12.13	0.163	0.226
Acreage**	-0.010	0.0162	-0.64	-0.042	0.022
Time**	0.691	0.0072	95.78	0.677	0.705
Constant	4.462	0.0690	64.70	4.327	4.597

R-squared: 0.5093

* The log-linear and semi-log regressions use 21,831 and 21,872 observations, respectively.
** These variables are dummy variables.

Table 9
BASIC REGRESSIONS FOR WAGE EQUATION
using regional dummy variables

LOG-LINEAR REGRESSION*

Hourly Wage	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Years of education	0.5369	0.01257	42.72	0.5123	0.5615
In school**	-0.0501	0.00753	-6.65	-0.0648	-0.0353
Speak English**	0.1251	0.01605	7.79	0.0936	0.1565
Sex**	-0.3085	0.00507	-60.88	-0.3185	-0.2986
Veteran status**	0.0550	0.00602	9.13	0.0432	0.0668
White**	0.0378	0.00636	5.95	0.0254	0.0503
Full-time**	-0.0222	0.00651	-3.41	-0.0350	-0.0095
Experience	0.1631	0.00254	64.15	0.1581	0.1681
Self-employed**	0.1503	0.01502	10.01	0.1208	0.1797
Time**	0.4812	0.00439	109.55	0.4726	0.4898
Constant	-0.1263	0.04359	-2.90	-0.2117	-0.0408
R-squared: 0.4478					

SEMI-LOG REGRESSION*

Hourly Wage	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Years of education	0.0569	0.00111	51.34	0.0547	0.0591
In school**	-0.0736	0.00702	-10.49	-0.0874	-0.0599
Speak English**	0.1338	0.01473	9.08	0.1049	0.1627
Sex**	-0.2977	0.00492	-60.52	-0.3074	-0.2881
Veteran status**	0.0499	0.00597	8.36	0.0382	0.0616
White**	0.0331	0.00624	5.31	0.0209	0.0454
Full-time**	-0.0212	0.00624	-3.40	-0.0335	-0.0090
Experience	0.0323	0.00059	54.62	0.0312	0.0335
Experience squared	-0.0005	0.00001	-36.07	-0.0005	-0.0005
Self-employed**	0.1471	0.01496	9.84	0.1178	0.1765
Time**	0.4734	0.00429	110.29	0.4650	0.4818
Constant	0.5970	0.03246	18.39	0.5334	0.6606
R-squared: 0.4666					

* The log-linear and semi-log regressions use 70,343 and 73,245 observations, respectively.
** These variables are dummy variables.

Table 10
BASIC REGRESSIONS FOR RENT EQUATION
using metropolitan area dummy variables

LOG-LINEAR REGRESSION*

Gross Rent	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Bedrooms	0.159	0.0178	8.92	0.124	0.194
Sewage**	0.056	0.0167	3.33	0.023	0.089
Kitchen**	-0.071	0.0367	-1.93	-0.143	0.001
Plumbing**	0.351	0.0534	6.58	0.247	0.456
Detached**	0.187	0.0083	22.43	0.170	0.203
Water**	0.100	0.0250	3.99	0.051	0.149
Building age	-0.114	0.0042	-27.42	-0.122	-0.106
Other rooms	0.314	0.0166	18.87	0.281	0.346
Condo**	0.180	0.0150	11.96	0.150	0.209
Acreage**	-0.030	0.0154	-1.97	-0.060	0.000
Time**	0.629	0.0100	62.92	0.610	0.649
Constant	4.748	0.0922	51.47	4.567	4.929

R-squared: 0.5532

SEMI-LOG REGRESSION*

Gross Rent	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Bedrooms	0.042	0.0065	6.38	0.029	0.055
Sewage**	0.057	0.0163	3.52	0.025	0.089
Kitchen**	-0.044	0.0370	-1.20	-0.117	0.028
Plumbing**	0.346	0.0528	6.56	0.243	0.449
Detached**	0.142	0.0085	16.66	0.125	0.159
Water**	0.090	0.0245	3.69	0.042	0.138
Building age	-0.006	0.0002	-27.70	-0.007	-0.006
Other rooms	0.102	0.0040	25.87	0.094	0.110
Condo**	0.173	0.0149	11.64	0.144	0.203
Acreage**	-0.023	0.0154	-1.52	-0.054	0.007
Time**	0.627	0.0101	62.28	0.608	0.647
Constant	4.621	0.0916	50.44	4.441	4.801

R-squared: 0.5582

* The log-linear and semi-log regressions use 21,831 and 21,872 observations, respectively.

** These variables are dummy variables.

Table 11
BASIC REGRESSIONS FOR WAGE EQUATION
using metropolitan area dummy variables

LOG-LINEAR REGRESSION*

Hourly Wage	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Years of education	0.5284	0.01247	42.39	0.5040	0.5529
In school**	-0.0551	0.00746	-7.39	-0.0697	-0.0405
Speak English**	0.1661	0.01610	10.32	0.1345	0.1976
Sex**	-0.3030	0.00504	-60.18	-0.3129	-0.2932
Veteran status**	0.0625	0.00596	10.49	0.0509	0.0742
White**	0.0598	0.00637	9.40	0.0474	0.0723
Full-time**	-0.0215	0.00649	-3.32	-0.0342	-0.0088
Experience	0.1615	0.00252	64.00	0.1566	0.1665
Self-employed**	0.1485	0.01494	9.95	0.1193	0.1778
Time**	0.4489	0.00644	69.73	0.4363	0.4615
Constant	-0.4445	0.06636	-6.70	-0.5746	-0.3144

R-squared: 0.4605

SEMI-LOG REGRESSION*

Hourly Wage	COEFF	STD ERR	T-STAT	95% CONFIDENCE INT	
Years of education	0.0558	0.00110	50.58	0.0536	0.0579
In school**	-0.0782	0.00695	-11.24	-0.0918	-0.0646
Speak English**	0.1757	0.01483	11.85	0.1466	0.2048
Sex**	-0.2926	0.00489	-59.83	-0.3022	-0.2831
Veteran status**	0.0578	0.00591	9.77	0.0462	0.0694
White**	0.0545	0.00624	8.72	0.0422	0.0667
Full-time**	-0.0206	0.00621	-3.32	-0.0328	-0.0084
Experience	0.0323	0.00059	54.96	0.0311	0.0334
Experience squared	-0.0005	0.00001	-36.53	-0.0005	-0.0005
Self-employed**	0.1457	0.01487	9.80	0.1165	0.1749
Time**	0.4405	0.00627	70.27	0.4282	0.4528
Constant	0.2655	0.05885	4.51	0.1502	0.3808

R-squared: 0.4786

* The log-linear and semi-log regressions use 70,343 and 73,245 observations, respectively.

** These variables are dummy variables.

Table 12
LOG-LINEAR REGRESSION WITH INDEX CRIMES FOR RENT EQUATION*
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Bedrooms	0.145	0.018	8.07	2.850	0.285	69.32
Sewage	0.094	0.017	5.45	0.955		469.69
Kitchen	-0.086	0.037	-2.34	0.992		-391.62
Plumbing	0.363	0.056	6.54	0.996		2087.55
Detached	0.179	0.008	21.35	0.191		937.27
Water	0.087	0.026	3.40	0.977		434.77
Building age	-0.109	0.004	-26.02	25.629	2.563	-52.14
Other rooms	0.313	0.017	18.62	4.176	0.418	149.60
Condo	0.184	0.015	11.97	0.038		961.76
Acreage	-0.029	0.016	-1.82	0.958		-134.58
Central city	-0.054	0.007	-7.90	0.577		-249.93
COLI	0.342	0.095	3.62	85.164	8.516	163.48
Manufacturing	-0.808	0.091	-8.88	20.133	2.013	-385.82
Unemployed	0.248	0.051	4.86	8.422	0.842	118.46
Vacancy	-0.596	0.066	-9.05	8.264	0.826	-284.44
Violent crimes	-0.084	0.021	-4.02	765.059	76.506	-39.86
Property crimes	-0.100	0.034	-2.94	5974.484	597.448	-47.76
Coastline	0.049	0.013	3.70	0.558		239.90
Pop density	0.050	0.010	5.11	1664.148	166.415	23.80
Superfund	0.031	0.006	4.92	80.128	8.013	14.72
TSP	0.046	0.030	1.51	63.471	6.347	21.83
Heating days	-0.035	0.018	-2.00	4178.979	417.898	-16.93
Cooling days	-0.144	0.023	-6.12	1294.445	129.445	-68.58
Precipitation	-0.113	0.018	-6.23	34.283	3.428	-53.87
Windspeed	-0.173	0.036	-4.76	9.243	0.924	-82.63
Humidity	-0.018	0.055	-0.32	55.731	5.573	-8.37
Sunshine	0.664	0.085	7.84	61.061	6.106	317.13
Commute time	0.208	0.030	6.85	25.331	2.533	99.29
T-P ratio	0.356	0.057	6.23	0.069	0.007	169.82
Intergov rev	-0.103	0.019	-5.32	834.804	83.480	-49.29
Local taxes	0.275	0.035	7.91	820.122	82.012	131.20
Property taxes	-0.147	0.030	-4.83	535.320	53.532	-70.09
Time	0.670	0.034	19.75	0.434		
Constant	6.802	0.757	8.98			

R-squared: 0.5403

* This regression uses 21,831 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4773.62 in the 1980-90 period.

Table 13
LOG-LINEAR REGRESSION WITH INDEX CRIMES FOR WAGE EQUATION*
using regional dummy variables

Hourly wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Years of education	0.532	0.012	42.59	13.303		
In school	-0.054	0.007	-7.29	0.091		
Speak English	0.165	0.016	10.30	0.979		
Sex	-0.303	0.005	-60.00	0.444		
Veteran status	0.061	0.006	10.29	0.192		
White	0.064	0.006	9.98	0.873		
Full-time	-0.021	0.006	-3.26	0.794		
Experience	0.161	0.003	63.70	18.399		
Self-employed	0.151	0.015	10.08	0.046		
Central city	0.036	0.004	8.57	0.536		1088.64
COLI	0.188	0.061	3.07	82.168	8.217	559.29
Manufacturing	0.025	0.052	0.49	18.754	1.875	75.30
Unemployment	0.187	0.029	6.49	7.782	0.778	556.61
Violent crimes	-0.018	0.011	-1.67	827.899	82.790	-53.72
Property crimes	-0.062	0.021	-3.02	5907.194	590.719	-184.52
Coastline	0.083	0.009	9.69	0.521		2570.37
Pop density	-0.001	0.006	-0.22	998.998	99.900	-3.84
Superfund	0.034	0.004	8.10	87.945	8.795	101.16
TSP	0.021	0.020	1.09	63.443	6.344	63.64
Heating days	0.088	0.013	6.87	3967.490	396.749	259.94
Cooling days	-0.021	0.015	-1.42	1354.516	135.452	-63.83
Precipitation	-0.031	0.014	-2.23	33.135	3.313	-90.64
Windspeed	-0.081	0.025	-3.20	8.894	0.889	-240.29
Humidity	-0.019	0.034	-0.57	56.024	5.602	-57.91
Sunshine	0.380	0.057	6.73	61.190	6.119	1130.30
Commute time	0.124	0.025	5.04	23.899	2.390	367.14
T-P ratio	0.048	0.034	1.41	0.072	0.007	141.55
Intergov rev	-0.045	0.011	-4.13	657.699	65.770	-132.72
Local taxes	0.099	0.019	5.13	685.199	68.520	292.92
Property taxes	-0.056	0.018	-3.20	472.142	47.214	-167.27
Time	0.514	0.018	28.29	0.655		
Constant	-3.132	0.448	-6.99			

R-squared: 0.4585

* This regression uses 70,343 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.94 and 1945.78 annual hours worked in the 1980-90 period.

Table 14
LOG-LINEAR REGRESSION WITH INDEX CRIMES FOR RENT EQUATION*
using metropolitan area dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Bedrooms	0.158	0.018	8.92	2.850	0.285	75.52
Sewage	0.070	0.017	4.15	0.955		345.45
Kitchen	-0.073	0.036	-2.01	0.992		-336.66
Plumbing	0.359	0.053	6.77	0.996		2064.36
Detached	0.179	0.008	21.69	0.191		937.38
Water	0.103	0.025	4.13	0.977		518.62
Building age	-0.107	0.004	-25.37	25.629	2.563	-50.90
Other rooms	0.309	0.017	18.61	4.176	0.418	147.51
Condo	0.181	0.015	12.12	0.038		948.41
Acreage	-0.026	0.015	-1.73	0.958		-124.15
Central city	-0.052	0.007	-7.58	0.577		-244.02
COLI	-1.060	0.668	-1.59	85.164	8.516	-506.17
Manufacturing	-0.886	0.329	-2.70	20.133	2.013	-423.07
Unemployed	0.498	0.203	2.45	8.422	0.842	237.49
Vacancy	0.021	0.205	0.10	8.264	0.826	10.19
Violent crimes	0.150	0.141	1.06	765.059	76.506	71.51
Property crimes	-0.180	0.229	-0.79	5974.484	597.448	-86.03
Coastline	1.996	1.892	1.06	0.558		30346.08
Pop density	0.022	0.065	0.34	1664.148	166.415	10.55
Superfund	0.028	0.032	0.87	80.128	8.013	13.26
TSP	0.034	0.136	0.25	63.471	6.347	16.28
Heating days	-0.996	1.359	-0.73	4178.979	417.898	-475.66
Cooling days	-0.435	0.660	-0.66	1294.445	129.445	-207.54
Precipitation	-0.280	1.064	-0.26	34.283	3.428	-133.58
Windspeed	0.886	0.528	1.68	9.243	0.924	422.99
Humidity	2.016	2.985	0.68	55.731	5.573	962.53
Sunshine	2.565	1.170	2.19	61.190	6.119	1224.24
Commute time	-0.397	0.129	-3.09	25.331	2.533	-189.49
T-P ratio	-0.104	0.252	-0.41	0.069	0.007	-49.56
Intergov rev	-0.091	0.121	-0.75	834.804	83.480	-43.62
Local taxes	1.107	0.204	5.43	820.122	82.012	528.42
Property taxes	-1.466	0.249	-5.90	535.320	53.532	-700.03
Time	0.858	0.134	6.40	0.434		
Constant	4.123	10.966	0.38			

R-squared: 0.5592

* This regression uses 21,831 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4773.62 in the 1980-90 period.

Table 15
LOG-LINEAR REGRESSION WITH INDEX CRIMES FOR WAGE EQUATION*
using metropolitan area dummy variables

Hourly wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Years of education	0.527	0.012	42.45	13.303		
In school	-0.056	0.007	-7.46	0.091		
Speak English	0.171	0.016	10.67	0.979		
Sex	-0.302	0.005	-60.03	0.444		
Veteran status	0.063	0.006	10.53	0.192		
White	0.067	0.006	10.41	0.873		
Full-time	-0.023	0.006	-3.49	0.794		
Experience	0.161	0.003	64.02	18.399		
Self-employed	0.150	0.015	10.03	0.046		
Central city	0.044	0.004	10.09	0.536		1334.83
COLI	0.395	0.436	0.91	82.168	8.217	1173.41
Manufacturing	-0.569	0.208	-2.74	18.754	1.875	-1690.61
Unemployment	-0.108	0.141	-0.76	7.782	0.778	-319.81
Violent crimes	-0.221	0.097	-2.28	827.899	82.790	-656.60
Property crimes	-0.023	0.157	-0.14	5907.194	590.719	-66.97
Coastline	4.018	1.958	2.05	0.521		1621136.88
Pop density	0.082	0.039	2.09	998.998	99.900	244.09
Superfund	0.026	0.014	1.86	87.945	8.795	77.66
TSP	0.021	0.066	0.32	63.443	6.344	62.66
Heating days	1.383	0.785	1.76	3967.490	396.749	4107.76
Cooling days	0.558	0.335	1.67	1354.516	135.452	1657.55
Precipitation	0.030	0.461	0.07	33.135	3.313	90.10
Windspeed	-0.122	0.247	-0.49	8.894	0.889	-362.79
Humidity	-1.304	1.345	-0.97	56.024	5.602	-3873.68
Sunshine	1.156	0.600	1.93	61.190	6.119	3434.99
Commute time	-0.072	0.110	-0.66	23.899	2.390	-214.74
T-P ratio	-0.169	0.147	-1.15	0.072	0.007	-502.73
Intergov rev	-0.071	0.056	-1.26	657.699	65.770	-210.67
Local taxes	0.250	0.123	2.04	685.199	68.520	741.23
Property taxes	-0.255	0.147	-1.74	472.142	47.214	-758.38
Time	0.393	0.079	4.99	0.655		
Constant	-14.126	7.829	-1.80			

R-squared: 0.4625

* This regression uses 70,343 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.94 and 1945.78 annual hours worked in the 1980-90 period.

Table 16
SEMI-LOG REGRESSION WITH INDEX CRIMES FOR RENT EQUATION*
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Bedrooms	0.0372139	0.006617	5.62	2.851	0.285	50.71
Sewage	0.0894882	0.016935	5.28	0.955		447.50
Kitchen	-0.0512006	0.036657	-1.40	0.992		-238.59
Plumbing	0.3604259	0.054799	6.58	0.996		2074.33
Detached	0.1340844	0.008597	15.60	0.191		685.91
Water	0.0874268	0.025117	3.48	0.977		436.73
Building age	-0.0060658	0.000234	-25.95	25.612	2.561	-74.26
Other rooms	0.1025789	0.004003	25.62	4.177	0.418	204.84
Condo	0.1754580	0.015033	11.67	0.038		916.81
Acreage	-0.0215002	0.015664	-1.37	0.958		-101.68
Central city	-0.0511650	0.006872	-7.45	0.578		-238.43
COLI	-0.0019129	0.001161	-1.65	85.196	8.520	-77.90
Manufacturing	-0.0178753	0.003545	-5.04	20.126	2.013	-171.98
Unemployed	0.0135671	0.006123	2.22	8.419	0.842	54.60
Vacancy	-0.0436198	0.006508	-6.70	8.263	0.826	-172.28
Violent crimes	0.0000008	0.000027	0.03	764.714	76.471	0.30
Property crimes	-0.0000003	0.000006	-0.06	5972.901	597.290	-0.88
Coastline	0.0300161	0.012148	2.47	0.559		145.66
Pop density	-0.0000303	0.000016	-1.88	1661.283	166.128	-24.06
Superfund	0.0010253	0.000090	11.38	80.006	8.001	39.21
TSP	-0.0004342	0.000456	-0.95	63.453	6.345	-13.17
Heating days	0.0000291	0.000008	3.46	4190.959	419.096	58.30
Cooling days	0.0000423	0.000014	2.93	1292.018	129.202	26.13
Precipitation	-0.0085331	0.000779	-10.96	34.248	3.425	-139.70
Windspeed	-0.0278460	0.004328	-6.43	9.239	0.924	-122.98
Humidity	0.0087790	0.001218	7.21	55.744	5.574	233.93
Sunshine	0.0030551	0.001535	1.99	61.027	6.103	89.12
Commute time	0.0091491	0.001206	7.59	25.314	2.531	110.71
T-P ratio	2.5816060	0.801063	3.22	0.069	0.007	85.21
Intergov rev	0.0000388	0.000046	0.84	835.428	83.543	15.49
Local taxes	0.0005495	0.000049	11.19	819.867	81.987	215.36
Property taxes	-0.0004891	0.000068	-7.23	535.467	53.547	-125.19
Time	0.6026081	0.037069	16.26	0.435		
Constant	4.5367190	0.272667	16.64			

R-squared: 0.5477

* This regression uses 21,872 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4780.22 in the 1980-90 period.

Table 17
SEMI-LOG REGRESSION WITH INDEX CRIMES FOR WAGE EQUATION*
using regional dummy variables

Hourly wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Years of education	0.056018	0.001103	50.79	13.242		
In school	-0.077018	0.006965	-11.06	0.110		
Speak English	0.177753	0.014825	11.99	0.978		
Sex	-0.291932	0.004895	-59.64	0.448		
Veteran status	0.057235	0.005924	9.66	0.185		
White	0.058983	0.006271	9.41	0.873		
Full-time	-0.021599	0.006200	-3.48	0.777		
Experience	0.032280	0.000585	55.19	17.851		
Experience sq	-0.000486	0.000013	-36.80	477.267		
Self-employed	0.147896	0.014897	9.93	0.045		
Central city	0.038507	0.004114	9.36	0.534		1147.86
COLI	0.002551	0.000765	3.33	82.199	8.220	613.08
Manufacturing	0.002108	0.002220	0.95	18.759	1.876	115.63
Unemployment	0.012316	0.003366	3.66	7.786	0.779	280.36
Violent crimes	0.000019	0.000015	1.24	827.165	82.716	46.19
Property crimes	-0.000005	0.000004	-1.32	5900.791	590.079	-79.54
Coastline	0.057419	0.007715	7.44	0.523		1727.99
Pop density	-0.000019	0.000008	-2.22	997.624	99.762	-54.55
Superfund	0.000554	0.000059	9.46	87.695	8.769	141.95
TSP	0.000125	0.000288	0.44	63.455	6.346	23.23
Heating days	0.000034	0.000005	6.48	3980.745	398.075	398.06
Cooling days	0.000001	0.000009	0.08	1350.140	135.014	3.07
Precipitation	-0.001243	0.000502	-2.48	33.072	3.307	-120.22
Windspeed	-0.011232	0.002823	-3.98	8.889	0.889	-291.91
Humidity	0.000558	0.000830	0.67	56.040	5.604	91.40
Sunshine	0.004926	0.000966	5.10	61.167	6.117	880.90
Commute time	0.008728	0.001121	7.79	23.873	2.387	609.23
T-P ratio	0.742399	0.431446	1.72	0.072	0.007	155.57
Intergov rev	-0.000034	0.000024	-1.41	658.781	65.878	-65.68
Local taxes	0.000159	0.000029	5.41	683.837	68.384	318.31
Property taxes	-0.000151	0.000040	-3.81	471.544	47.154	-207.50
Time	0.460073	0.017352	26.51	0.654		
Constant	-0.473456	0.171951	-2.75			

R-squared: 0.4772

* This regression uses 73,245 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.71 and 1912.73 annual hours worked in the 1980-90 period.

Table 18
SEMI-LOG REGRESSION WITH INDEX CRIMES FOR RENT EQUATION*
using metropolitan area dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Bedrooms	0.04219	0.00651	6.48	2.851	0.285	57.49
Sewage	0.07017	0.01638	4.28	0.955		347.50
Kitchen	-0.04680	0.03687	-1.27	0.992		-218.57
Plumbing	0.35408	0.05251	6.74	0.996		2030.99
Detached	0.13443	0.00845	15.91	0.191		687.81
Water	0.09214	0.02455	3.75	0.977		461.38
Building age	-0.00588	0.00023	-25.25	25.612	2.561	-71.98
Other rooms	0.10133	0.00394	25.72	4.177	0.418	202.34
Condo	0.17619	0.01484	11.87	0.038		921.00
Acreage	-0.01850	0.01531	-1.21	0.958		-87.63
Central city	-0.05160	0.00699	-7.38	0.578		-240.41
COLI	-0.01803	0.00881	-2.05	85.196	8.520	-734.29
Manufacturing	-0.07060	0.01954	-3.61	20.126	2.013	-679.28
Unemployed	0.07488	0.01684	4.45	8.419	0.842	301.37
Vacancy	0.01231	0.03292	0.37	8.263	0.826	48.63
Violent crimes	0.00045	0.00024	1.87	764.714	76.471	162.71
Property crimes	-0.00011	0.00004	-2.81	5972.901	597.290	-327.77
Coastline	-2.85228	2.33625	-1.22	0.559		-4504.34
Pop density	0.00039	0.00023	1.71	1661.283	166.128	309.00
Superfund	-0.00066	0.00064	-1.02	80.006	8.001	-25.07
TSP	-0.00038	0.00233	-0.16	63.453	6.345	-11.51
Heating days	0.00059	0.00052	1.14	4190.959	419.096	1174.78
Cooling days	0.00027	0.00089	0.30	1292.018	129.202	165.89
Precipitation	-0.04944	0.02910	-1.70	34.248	3.425	-809.34
Windspeed	0.13537	0.06605	2.05	9.239	0.924	597.83
Humidity	0.04282	0.05835	0.73	55.744	5.574	1140.95
Sunshine	0.07095	0.01798	3.95	61.027	6.103	2069.74
Commute time	-0.00302	0.00528	-0.57	25.314	2.531	-36.51
T-P ratio	2.13318	3.05796	0.70	0.069	0.007	70.41
Intergov rev	0.00015	0.00028	0.55	835.428	83.543	60.86
Local taxes	-0.00009	0.00036	-0.27	819.867	81.987	-37.08
Property taxes	-0.00059	0.00037	-1.60	535.467	53.547	-150.53
Time	0.65706	0.15296	4.30	0.435		
Constant	-1.59599	2.15482	-0.74			

R-squared: 0.5645

* This regression uses 21,872 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4780.22 in the 1980-90 period.

Table 19
SEMI-LOG REGRESSION WITH INDEX CRIMES FOR WAGE EQUATION*
using metropolitan area dummy variables

Hourly wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Years of education	0.055473	0.00110	50.42	13.242		
In school	-0.077918	0.00695	-11.21	0.110		
Speak English	0.181216	0.01481	12.24	0.978		
Sex	-0.291501	0.00488	-59.68	0.448		
Veteran status	0.057993	0.00591	9.82	0.185		
White	0.061574	0.00626	9.83	0.873		
Full-time	-0.021877	0.00620	-3.53	0.777		
Experience	0.032328	0.00058	55.31	17.851		
Experience sq	-0.000487	0.00001	-36.87	477.267		
Self-employed	0.147041	0.01487	9.89	0.045		
Central city	0.043913	0.00424	10.35	0.534		1312.56
COLI	-0.001348	0.00546	-0.25	82.199	8.220	-324.07
Manufacturing	-0.035525	0.00833	-4.27	18.759	1.876	-1948.48
Unemployment	0.026463	0.01030	2.57	7.786	0.779	602.41
Violent crimes	-0.000319	0.00013	-2.49	827.165	82.716	-772.47
Property crimes	-0.000027	0.00003	-1.04	5900.791	590.079	-460.66
Coastline	-0.604805	1.15023	-0.53	0.523		-13269.05
Pop density	0.000420	0.00011	3.84	997.624	99.762	1225.40
Superfund	-0.000269	0.00024	-1.14	87.695	8.769	-68.90
TSP	-0.001344	0.00101	-1.33	63.455	6.346	-249.38
Heating days	0.000363	0.00023	1.59	3980.745	398.075	4226.18
Cooling days	0.000353	0.00037	0.96	1350.140	135.014	1394.30
Precipitation	-0.013623	0.01009	-1.35	33.072	3.307	-1317.26
Windspeed	0.020786	0.02645	0.79	8.889	0.889	540.21
Humidity	0.008635	0.02041	0.42	56.040	5.604	1414.92
Sunshine	0.030363	0.00863	3.52	61.167	6.117	5430.22
Commute time	-0.002147	0.00409	-0.53	23.873	2.387	-149.87
T-P ratio	-1.913853	2.00182	-0.96	0.072	0.007	-401.06
Intergov rev	-0.000097	0.00010	-0.97	658.781	65.878	-187.42
Local taxes	-0.000009	0.00013	-0.07	683.837	68.384	-18.71
Property taxes	-0.000178	0.00018	-0.97	471.544	47.154	-245.28
Time	0.522193	0.04994	10.46	0.654		
Constant	-3.134664	1.53888	-2.04			

R-squared: 0.4806

* This regression uses 73,245 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.71 and 1912.73 annual hours worked in the 1980-90 period.

Table 20
LOG-LINEAR REGRESSIONS BY GENDER FOR WAGE EQUATION
using regional dummy variables

	Female*			Male*		
Hourly wage	COEFF**	T-STAT	MEAN	COEFF	T-STAT	MEAN
Years of education	0.518	24.914	13.314	0.558	35.867	13.295
In school	-0.022	-2.198	0.100	-0.089	-8.079	0.084
Speak English	0.099	3.656	0.982	0.215	10.918	0.976
Veteran status	0.028	1.040	0.014	-0.002	-0.294	0.335
White	0.022	2.473	0.856	0.115	12.439	0.887
Full-time	-0.014	-1.956	0.678	-0.074	-5.792	0.888
Experience	0.104	31.804	18.061	0.228	57.950	18.669
Self-employed	0.095	3.164	0.025	0.146	8.509	0.063
Central city	0.060	9.950	0.541	0.010	1.735	0.532
COLI	0.259	2.908	82.208	0.108	1.316	82.135
Manufacturing	-0.026	-0.355	18.709	0.069	0.981	18.790
Unemployment	0.159	3.859	7.737	0.203	5.167	7.818
Violent crimes	-0.009	-0.625	823.816	-0.029	-1.935	831.165
Property crimes	-0.053	-1.815	5887.015	-0.062	-2.235	5923.335
Coastline	0.047	3.811	0.519	0.113	9.712	0.523
Pop density	0.006	0.747	992.987	-0.007	-0.822	1003.806
Superfund	0.021	3.368	88.494	0.045	7.954	87.506
TSP	0.022	0.775	62.992	0.027	0.994	63.803
Heating days	0.076	4.225	3992.697	0.099	5.623	3947.326
Cooling days	-0.027	-1.276	1350.263	-0.011	-0.527	1357.917
Precipitation	-0.068	-3.435	33.337	-0.003	-0.170	32.973
Windspeed	-0.079	-2.222	8.910	-0.084	-2.451	8.882
Humidity	-0.011	-0.230	56.031	-0.026	-0.543	56.019
Sunshine	0.285	3.500	61.081	0.438	5.690	61.277
Commute time	0.205	5.824	23.883	0.047	1.430	23.911
T-P ratio	0.004	0.088	0.072	0.087	1.919	0.071
Intergov rev	-0.020	-1.317	659.292	-0.063	-4.231	656.426
Local taxes	0.069	2.579	691.327	0.123	4.656	680.297
Property taxes	-0.027	-1.094	476.078	-0.081	-3.369	468.993
Time	0.553	21.311	0.668	0.479	19.301	0.645
Constant	-3.154	-4.952		-3.177	-5.185	
	R-squared:	0.4421		R-squared:	0.4250	
Mean hourly wage***			9.62			13.80
Annual hours***			1756.05			2097.54

* These regressions for females and males use 31,262 and 39,081 observations, respectively.

** A negative coefficient classifies that independent variable as an amenity.

*** These variable are in terms of the 1980-90 period.

Table 21
LOG-LINEAR REGRESSION WITH ALL CRIMES FOR RENT EQUATION*
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	-0.050	0.007	-7.40	0.58		-235.07
COLI	0.475	0.100	4.73	85.16	8.516	226.52
Manufacturing	-0.736	0.091	-8.10	20.13	2.013	-351.53
Unemployed	0.101	0.057	1.79	8.42	0.842	48.31
Vacancy	-0.688	0.071	-9.68	8.26	0.826	-328.29
Murder	0.054	0.016	3.43	13.32	1.332	25.59
Rape	0.061	0.022	2.81	45.80	4.580	29.28
Robbery	0.090	0.016	5.79	270.55	27.055	42.86
Agg assault	-0.146	0.015	-9.49	435.39	43.539	-69.53
Burglary	-0.318	0.035	-9.00	1809.20	180.920	-152.00
Larceny	0.141	0.033	4.22	3508.03	350.803	67.29
Auto theft	-0.113	0.017	-6.61	657.25	65.725	-53.93
Coastline	0.011	0.014	0.75	0.56		51.64
Pop density	0.028	0.010	2.94	1664.15	166.415	13.60
Superfund	0.056	0.007	7.68	80.13	8.013	26.60
TSP	-0.036	0.032	-1.12	63.47	6.347	-17.15
Heating days	-0.077	0.018	-4.26	4178.98	417.898	-36.78
Cooling days	-0.164	0.024	-6.73	1294.45	129.445	-78.09
Precipitation	-0.105	0.018	-5.71	34.28	3.428	-50.07
Windspeed	-0.115	0.037	-3.11	9.24	0.924	-54.74
Humidity	0.186	0.056	3.32	55.73	5.573	88.61
Sunshine	0.923	0.088	10.54	61.06	6.106	440.47
Commute time	0.275	0.032	8.58	25.33	2.533	131.22
T-P ratio	0.330	0.057	5.83	0.07	0.007	157.77
Intergov rev	-0.030	0.022	-1.37	834.80	83.480	-14.22
Local taxes	0.147	0.038	3.92	820.12	82.012	70.37
Property taxes	-0.018	0.033	-0.53	535.32	53.532	-8.39
Time	0.550	0.042	13.03	0.43		
Constant	5.173	0.817	6.33			

R-squared: 0.5452

* This regression uses 21,831 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount, including utilities, of $4773.62 in the 1980-90 period.

Table 22

LOG-LINEAR REGRESSION WITH ALL CRIMES FOR WAGE EQUATION*

using regional dummy variables

Hourly Wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	0.040	0.004	9.38	0.536		1201.51
COLI	0.346	0.066	5.27	82.168	8.217	1027.96
Manufacturing	0.104	0.054	1.92	18.754	1.875	308.68
Unemployed	0.118	0.032	3.68	7.782	0.778	351.36
Murder	-0.001	0.009	-0.15	12.460	1.246	-4.03
Rape	0.024	0.013	1.80	47.091	4.709	71.52
Robbery	0.032	0.009	3.43	311.212	31.121	94.06
Agg assault	-0.025	0.010	-2.51	457.137	45.714	-73.56
Burglary	-0.193	0.022	-8.93	1599.804	159.980	-573.03
Larceny	0.091	0.020	4.45	3534.790	353.479	269.54
Auto theft	-0.024	0.010	-2.42	772.599	77.260	-70.60
Coastline	0.074	0.009	8.15	0.521		2265.78
Pop density	-0.010	0.006	-1.66	998.998	99.900	-30.06
Superfund	0.044	0.005	9.19	87.945	8.795	130.87
TSP	0.017	0.020	0.82	63.443	6.344	49.42
Heating days	0.053	0.013	3.94	3967.490	396.749	155.99
Cooling days	-0.033	0.016	-2.05	1354.516	135.452	-98.17
Precipitation	0.011	0.015	0.73	33.135	3.313	33.01
Windspeed	-0.053	0.026	-2.04	8.894	0.889	-156.93
Humidity	0.033	0.036	0.93	56.024	5.602	98.33
Sunshine	0.550	0.061	9.06	61.190	6.119	1632.65
Commute time	0.147	0.026	5.71	23.899	2.390	436.49
T-P ratio	0.063	0.034	1.84	0.072	0.007	187.64
Intergov rev	-0.026	0.012	-2.21	657.699	65.770	-76.57
Local taxes	0.069	0.021	3.34	685.199	68.520	206.07
Property taxes	-0.025	0.019	-1.31	472.142	47.214	-75.53
Time	0.425	0.021	20.69	0.655		
Constant	-4.674	0.496	-9.43			

R-squared: 0.4593

* This regression uses 70,343 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.94 and 1945.78 annual hours worked in the 1980-90 period.

Table 23
SEMI-LOG REGRESSION WITH ALL CRIMES FOR RENT EQUATION*
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	-0.051734	0.006888	-7.51	0.578		-241.01
COLI	-0.002177	0.001234	-1.76	85.196	8.520	-88.66
Manufacturing	-0.020931	0.003612	-5.80	20.126	2.013	-201.37
Unemployed	0.018030	0.006552	2.75	8.419	0.842	72.56
Vacancy	-0.053341	0.007351	-7.26	8.263	0.826	-210.68
Murder	0.003252	0.001775	1.83	13.304	1.330	20.68
Rape	0.001929	0.000457	4.22	45.879	4.588	42.30
Robbery	0.000272	0.000054	5.04	270.329	27.033	35.11
Agg assault	-0.000309	0.000045	-6.93	435.203	43.520	-64.35
Burglary	-0.000140	0.000023	-5.98	1807.489	180.749	-120.70
Larceny	0.000033	0.000009	3.56	3508.137	350.814	54.84
Auto theft	-0.000034	0.000025	-1.40	657.276	65.728	-10.81
Coastline	0.001895	0.013110	0.15	0.559		9.07
Pop density	-0.000008	0.000018	-0.42	1661.283	166.128	-5.96
Superfund	0.000866	0.000106	8.20	80.006	8.001	33.11
TSP	-0.000635	0.000462	-1.38	63.453	6.345	-19.26
Heating days	0.000020	0.000009	2.25	4190.959	419.096	40.87
Cooling days	0.000048	0.000016	3.08	1292.018	129.202	29.89
Precipitation	-0.008272	0.000831	-9.95	34.248	3.425	-135.43
Windspeed	-0.021277	0.004371	-4.87	9.239	0.924	-93.96
Humidity	0.013478	0.001367	9.86	55.744	5.574	359.14
Sunshine	0.006953	0.001581	4.40	61.027	6.103	202.83
Commute time	0.007891	0.001265	6.24	25.314	2.531	95.49
T-P ratio	1.485309	0.830475	1.79	0.069	0.007	49.03
Intergov rev	0.000072	0.000046	1.57	835.428	83.543	28.79
Local taxes	0.000440	0.000055	7.97	819.867	81.987	172.29
Property taxes	-0.000296	0.000075	-3.97	535.467	53.547	-75.74
Time	0.586086	0.047913	12.23	0.435		
Constant	4.236275	0.273983	15.46			

R-squared: 0.5504

* This regression uses 21,872 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4780.22 in the 1980-90 period.

Table 24
SEMI-LOG REGRESSION WITH ALL CRIMES FOR WAGE EQUATION*
using regional dummy variables

Hourly Wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	0.0384557	0.004120	9.33	0.534		1146.29
COLI	0.0029729	0.000799	3.72	82.199	8.220	714.50
Manufacturing	0.0026918	0.002378	1.13	18.759	1.876	147.64
Unemployed	0.0108193	0.003604	3.00	7.786	0.779	246.29
Murder	0.0008967	0.001024	0.88	12.439	1.244	32.61
Rape	0.0003955	0.000259	1.53	47.121	4.712	54.49
Robbery	0.0001006	0.000038	2.64	310.786	31.079	91.41
Agg assault	-0.0000490	0.000028	-1.75	456.819	45.682	-65.45
Burglary	-0.0000450	0.000014	-3.34	1597.663	159.766	-210.21
Larceny	0.0000081	0.000006	1.42	3531.458	353.146	83.64
Auto theft	-0.0000258	0.000014	-1.85	771.669	77.167	-58.21
Coastline	0.0526827	0.008202	6.42	0.523		1581.67
Pop density	-0.0000197	0.000009	-2.09	997.624	99.762	-57.46
Superfund	0.0005474	0.000068	8.01	87.695	8.769	140.36
TSP	0.0001157	0.000294	0.39	63.455	6.346	21.47
Heating days	0.0000287	0.000006	5.05	3980.745	398.075	334.04
Cooling days	0.0000001	0.000010	0.01	1350.140	135.014	0.34
Precipitation	-0.0009641	0.000574	-1.68	33.072	3.307	-93.23
Windspeed	-0.0087621	0.002941	-2.98	8.889	0.889	-227.72
Humidity	0.0017004	0.000920	1.85	56.040	5.604	278.62
Sunshine	0.0058195	0.001018	5.72	61.167	6.117	1040.78
Commute time	0.0084496	0.001234	6.85	23.873	2.387	589.79
T-P ratio	0.3445936	0.437350	0.79	0.072	0.007	72.21
Intergov rev	-0.0000147	0.000025	-0.59	658.781	65.878	-28.31
Local taxes	0.0001276	0.000033	3.82	683.837	68.384	255.13
Property taxes	-0.0000934	0.000044	-2.13	471.544	47.154	-128.77
Time	0.4445657	0.021086	21.08	0.654		
Constant	-0.5991217	0.181247	-3.31			

R-squared: 0.4774

* This regression uses 73,245 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.71 and 1912.73 annual hours worked in the 1980-90 period.

Table 25
LOG-LINEAR REGRESSION WITH ALL CRIMES FOR RENT EQUATION*
FOR 1990 ONLY
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	-0.017	0.010	-1.59	0.449		-113.40
COLI	0.034	0.271	0.12	82.270	8.227	23.16
Manufacturing	16.751	37.390	0.45	16.598	1.660	11522.77
Unemployed	-6.805	18.374	-0.37	6.743	0.674	-4681.17
Vacancy	13.839	28.198	0.49	10.052	1.005	9519.80
Murder	0.082	0.063	1.30	12.377	1.238	56.30
Rape	0.170	0.059	2.88	49.412	4.941	116.93
Robbery	-0.127	0.058	-2.17	368.894	36.889	-87.11
Agg assault	-0.201	0.047	-4.22	524.347	52.435	-137.93
Burglary	-0.575	0.106	-5.40	1411.052	141.105	-395.65
Larceny	0.326	0.071	4.60	3525.215	352.522	224.00
Auto theft	-0.018	0.035	-0.52	965.395	96.539	-12.43
Coastline	-0.059	0.027	-2.22	0.534		-394.49
Pop density	0.162	0.034	4.71	871.564	87.156	111.39
Superfund	0.139	0.036	3.87	113.922	11.392	95.45
TSP	-0.077	0.067	-1.16	61.983	6.198	-53.27
Heating days	-0.405	0.049	-8.18	3504.364	350.436	-278.52
Cooling days	-0.564	0.059	-9.57	1442.606	144.261	-387.63
Precipitation	-0.186	0.035	-5.37	31.149	3.115	-128.27
Windspeed	-0.303	0.109	-2.78	8.647	0.865	-208.40
Humidity	-1.206	0.194	-6.22	55.877	5.588	-829.89
Sunshine	1.190	0.184	6.47	61.994	6.199	818.59
Commute time	0.072	0.051	1.42	25.046	2.505	49.43
T-P ratio	0.565	0.135	4.19	0.074	0.007	388.71
Intergov rev	-0.047	0.058	-0.81	694.896	69.490	-32.65
Local taxes	0.251	0.098	2.56	729.426	72.943	172.33
Property taxes	-0.085	0.088	-0.97	503.848	50.385	-58.55
Constant	-52.973	141.760	-0.37			

R-squared: 0.3632

* This regression uses 9466 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $6878.94 in 1990.

Table 26
LOG-LINEAR REGRESSION WITH ALL CRIMES FOR WAGE EQUATION*
FOR 1990 ONLY
using regional dummy variables

Hourly Wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Central city	0.044	0.005	8.02	0.508		1596.48
COLI	0.089	0.132	0.68	81.588	8.159	317.35
Manufacturing	0.135	0.177	0.76	16.786	1.679	478.40
Unemployed	0.399	0.395	1.01	6.735	0.674	1419.53
Murder	-0.009	0.024	-0.39	12.493	1.249	-33.46
Rape	0.060	0.028	2.15	49.466	4.947	212.33
Robbery	0.087	0.026	3.32	358.535	35.854	310.64
Agg assault	-0.160	0.024	-6.53	523.533	52.353	-568.21
Burglary	-0.150	0.051	-2.94	1407.920	140.792	-532.00
Larceny	0.147	0.033	4.43	3543.554	354.355	521.54
Auto theft	-0.070	0.023	-3.08	927.168	92.717	-249.72
Coastline	0.012	0.017	0.74	0.556		439.53
Pop density	0.012	0.019	0.66	857.100	85.710	43.85
Superfund	0.093	0.017	5.39	105.954	10.595	330.76
TSP	-0.102	0.036	-2.83	61.421	6.142	-361.60
Heating days	-0.004	0.031	-0.12	3606.575	360.658	-13.62
Cooling days	-0.092	0.031	-2.97	1397.024	139.702	-325.90
Precipitation	-0.077	0.027	-2.88	31.941	3.194	-272.42
Windspeed	-0.171	0.068	-2.51	8.651	0.865	-608.22
Humidity	-0.047	0.119	-0.39	56.443	5.644	-165.87
Sunshine	0.681	0.123	5.55	61.448	6.145	2420.51
Commute time	0.167	0.045	3.69	24.372	2.437	593.80
T-P ratio	0.109	0.076	1.44	0.076	0.008	388.42
Intergov rev	-0.015	0.033	-0.45	684.674	68.467	-52.83
Local taxes	0.140	0.047	2.96	743.384	74.338	496.22
Property taxes	-0.085	0.045	-1.89	514.525	51.453	-300.36
Constant	-3.015	1.602	-1.88			

R-squared: 0.3541

* This regression uses 46,082 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $14.00 and 1977.55 annual hours worked in 1990.

Table 27
RESTRICTED LOG-LINEAR REGRESSION WITH ALL CRIMES FOR RENT EQUATION*
using regional dummy variables

Gross Rent	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Manufacturing	-0.599	0.058	-10.33	19.991	1.999	-288.78
Unemployed	0.192	0.036	5.40	8.340	0.834	92.50
Vacancy	-0.664	0.045	-14.84	8.370	0.837	-319.88
Murder	0.045	0.009	4.97	13.060	1.306	21.56
Rape	0.023	0.013	1.80	47.311	4.731	11.25
Robbery	0.040	0.008	4.83	338.839	33.884	19.37
Agg assault	-0.099	0.010	-9.62	437.423	43.742	-47.93
Burglary	-0.184	0.021	-8.71	1748.070	174.807	-88.47
Larceny	0.049	0.020	2.50	3542.578	354.258	23.63
Auto theft	-0.074	0.010	-7.12	736.630	73.663	-35.89
Coastline	0.029	0.010	3.02	0.507		141.36
Pop density	0.051	0.007	7.79	1578.444	157.844	24.62
Superfund	0.039	0.005	8.46	91.068	9.107	18.84
TSP	0.011	0.019	0.58	63.556	6.356	5.44
Heating days	-0.074	0.010	-7.76	4179.249	417.925	-35.73
Cooling days	-0.047	0.008	-5.64	1234.806	123.481	-22.85
Precipitation	-0.106	0.014	-7.85	34.205	3.421	-51.27
Windspeed	0.045	0.025	1.83	9.367	0.937	21.78
Humidity	-0.013	0.034	-0.38	56.206	5.621	-6.32
Sunshine	0.217	0.046	4.68	61.301	6.130	104.60
T-P ratio	0.017	0.033	0.52	0.071	0.007	8.23
Intergov rev	-0.003	0.012	-0.20	826.727	82.673	-1.21
Local taxes	0.217	0.024	9.12	882.981	88.298	104.53
Property taxes	-0.094	0.021	-4.39	551.909	55.191	-45.39
Time	0.688	0.024	28.25	0.459		
Constant	8.231	0.447	18.42			

R-squared: 0.4931

* This regression uses 41,179 observations.

** A positive coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean yearly rental amount of $4818.57 in the 1980-90 period.

Table 28
RESTRICTED LOG-LINEAR REGRESSION WITH ALL CRIMES FOR WAGE EQUATION*
using regional dummy variables

Hourly Wage	COEFF**	STD ERR	T-STAT	MEAN	10% CHG	DIFF***
Manufacturing	-0.100	0.040	-2.51	19.261	1.926	-294.67
Unemployed	0.112	0.022	5.20	8.014	0.801	330.00
Murder	0.032	0.006	4.96	12.767	1.277	93.88
Rape	0.002	0.009	0.22	46.666	4.667	6.01
Robbery	0.023	0.006	3.54	363.727	36.373	67.13
Agg assault	-0.022	0.008	-2.71	450.593	45.059	-63.44
Burglary	-0.139	0.016	-8.69	1603.653	160.365	-409.87
Larceny	0.059	0.014	4.09	3491.983	349.198	174.08
Auto theft	0.001	0.007	0.20	811.861	81.186	4.34
Coastline	0.032	0.007	4.64	0.602		956.30
Pop density	0.009	0.005	1.80	1306.337	130.634	25.36
Superfund	0.018	0.004	5.19	102.078	10.208	53.76
TSP	0.032	0.015	2.13	62.721	6.272	93.39
Heating days	0.028	0.008	3.42	4166.520	416.652	81.65
Cooling days	-0.019	0.007	-2.73	1225.265	122.527	-55.29
Precipitation	0.007	0.011	0.63	33.846	3.385	20.29
Windspeed	-0.032	0.020	-1.58	9.218	0.922	-94.43
Humidity	-0.072	0.028	-2.57	56.765	5.677	-212.26
Sunshine	0.128	0.038	3.41	60.749	6.075	376.98
T-P ratio	-0.114	0.027	-4.21	0.072	0.007	-335.34
Intergov rev	0.029	0.008	3.56	778.953	77.895	85.19
Local taxes	0.065	0.016	4.00	863.980	86.398	191.04
Property taxes	-0.014	0.015	-0.90	543.006	54.301	-40.17
Time	0.428	0.015	29.11	0.595		
Constant	-0.952	0.329	-2.90			

R-squared: 0.4646

* This regression uses 103,005 observations.

** A negative coefficient classifies that independent variable as an amenity.

*** Annual change based upon a mean hourly wage rate of $11.93 and 1933.96 annual hours worked in the 1980-90 period.

Table 29
CORRELATION COEFFICIENTS OF THE CRIME VARIABLES

RENT EQUATION

	Violent crimes	Murder	Rape	Robbery	Agg assault	Property crimes	Burglary	Larceny	Auto
Violent crimes	1.00								
Murder		1.00							
Rape		0.40	1.00						
Robbery		0.59	0.27	1.00					
Agg assault		0.56	0.39	0.62	1.00				
Property crimes	0.47					1.00			
Burglary		0.51	0.50	0.08	0.28		1.00		
Larceny		0.12	0.50	0.10	0.24		0.47	1.00	
Auto theft		0.42	0.19	0.80	0.51		-0.05	0.03	1.00

WAGE EQUATION

	Violent crimes	Murder	Rape	Robbery	Agg assault	Property crimes	Burglary	Larceny	Auto
Violent crimes	1.00								
Murder		1.00							
Rape		0.47	1.00						
Robbery		0.72	0.26	1.00					
Agg assault		0.60	0.39	0.69	1.00				
Property crimes	0.42					1.00			
Burglary		0.44	0.57	0.11	0.20		1.00		
Larceny		0.17	0.52	0.06	0.18		0.59	1.00	
Auto theft		0.58	0.22	0.78	0.58		0.02	0.02	1.00

Table 30
TOTAL COSTS PER HOUSEHOLD OF CRIME VARIABLES IN LOG-LINEAR REGRESSIONS

Index crimes using regions

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	39.86	*	-53.72		-13.86
Property crimes	47.76	*	-184.52		-136.76

- cost figures for rent and wage equations come from Tables 12-13

Index crimes using metropolitan areas

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	-71.51		-656.60		-728.11
Property crimes	86.03		-66.97		19.06

- cost figures for rent and wage equations come from Tables 14-15

All crimes

Crime Variables**	Rent eq		Wage eq		Total effect
Murder	-25.59		-4.03		-29.62
Rape	-29.28		71.52		42.24
Robbery	-42.86		94.06	*	51.20
Aggravated assault	69.53	*	-73.56		-4.03
Burglary	152.00	*	-573.03		-421.03
Larceny	-67.29		269.54	*	202.25
Auto theft	53.93	*	-70.60		-16.67

- cost figures for rent and wage equations come from Tables 21-22

* These variables are correctly classified as disamenities at the five percent significance level in the regressions.

** Dollar amounts are the mean annual household costs for ten percent increases in the independent variables.

Table 31
TOTAL COSTS PER HOUSEHOLD OF CRIME VARIABLES IN SEMI-LOG REGRESSIONS

Index crimes using regions

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	-0.30		46.19		45.89
Property crimes	0.88		-79.54		-78.66

- cost figures for rent and wage equations come from Tables 16-17

Index crimes using metropolitan areas

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	-162.71		-772.47		-935.18
Property crimes	327.77	*	-460.66		-132.89

- cost figures for rent and wage equations come from Tables 18-19

All crimes

Crime Variables**	Rent eq		Wage eq		Total effect
Murder	-20.68		32.61		11.93
Rape	-42.30		54.49		12.19
Robbery	-35.11		91.41	*	56.30
Agg assault	64.35	*	-65.45		-1.10
Burglary	120.70	*	-210.21		-89.51
Larceny	-54.84		83.64		28.80
Auto theft	10.81		-58.21		-47.40

- cost figures for rent and wage equations come from Tables 23-24

* These variables are correctly classified as disamenities at the five percent significance level in the regressions.

** Dollar amounts are the mean annual household costs for ten percent increases in the independent variables.

Table 32
TOTAL COSTS PER HOUSEHOLD OF CRIME VARIABLES IN LOG-LINEAR REGRESSIONS
using metropolitan area percentage changes for the Manufacturing, Unemployment, and Vacancy variables

Index crimes using regions

Crime Variables**	Rent eq	Wage eq	Total effect
Violent crimes	-6.20	22.91	16.71
Property crimes	-22.79	-15.91	-38.70

Index crimes using metropolitan areas

Crime Variables**	Rent eq	Wage eq	Total effect
Violent crimes	-26.78	-625.61	-652.39
Property crimes	-330.15	739.20	409.05

All crimes

Crime Variables**	Rent eq	Wage eq	Total effect
Murder	-21.69	29.30	7.61
Rape	27.06 *	-8.62	18.44
Robbery	-49.51	136.69 *	87.18
Aggravated assault	19.46 *	-36.08	-16.62
Burglary	109.18 *	-519.90	-410.72
Larceny	-84.74	380.39 *	295.65
Auto theft	19.41 *	-67.01	-47.60

* These variables are correctly classified as disamenities at the five percent significance level in the regressions.

** Dollar amounts are the mean annual household costs for ten percent increases in the independent variables.

Table 33

TOTAL COSTS PER HOUSEHOLD OF CRIME VARIABLES IN SEMI-LOG REGRESSIONS

using metropolitan area percentages for the Manufacturing, Unemployment, and Vacancy variables

Index crimes using regions

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	-27.27		93.11	*	65.84
Property crimes	-40.54		-57.11		-97.65

Index crimes using metropolitan areas

Crime Variables**	Rent eq		Wage eq		Total effect
Violent crimes	-80.71		-999.33		-1080.04
Property crimes	2.18		605.58		607.76

All crimes

Crime Variables**	Rent eq		Wage eq		Total effect
Murder	-36.46		33.78		-2.68
Rape	-11.82		15.86		4.04
Robbery	-24.40		117.77	*	93.37
Agg assault	17.85		-37.53		-19.68
Burglary	129.43	*	-210.21		-80.78
Larceny	-88.21		206.51	*	118.30
Auto theft	-20.05		-28.65		-48.70

* These variables are correctly classified as disamenities at the five percent significance level in the regressions.

** Dollar amounts are the mean annual household costs for ten percent increases in the independent variables.

Table 34

LOG-LINEAR REGRESSION WITH ALL CRIMES FOR RENT EQUATION for the bottom and top quartiles in family income

	Bottom Quartile*			Top Quartile*		
Gross Rent	COEFF**	STD ERR	T-STAT	COEFF	STD ERR	T-STAT
Central city	-0.072	0.018	-4.00	0.006	0.010	0.61
COLI	0.269	0.259	1.04	0.767	0.153	5.01
Manufacturing	-0.684	0.219	-3.13	-0.746	0.157	-4.74
Unemployed	0.143	0.137	1.04	0.079	0.091	0.87
Vacancy	-0.839	0.196	-4.28	-0.518	0.111	-4.66
Murder	-0.010	0.037	-0.28	0.088	0.028	3.12
Rape	0.098	0.054	1.81	-0.024	0.036	-0.66
Robbery	0.085	0.037	2.26	0.036	0.025	1.44
Agg assault	-0.214	0.038	-5.70	-0.065	0.025	-2.59
Burglary	-0.196	0.090	-2.19	-0.296	0.064	-4.64
Larceny	0.141	0.082	1.71	0.147	0.056	2.63
Auto theft	-0.117	0.042	-2.82	-0.068	0.027	-2.55
Coastline	0.015	0.037	0.40	0.032	0.024	1.33
Pop density	0.049	0.022	2.21	0.032	0.016	2.01
Superfund	0.054	0.017	3.19	0.029	0.012	2.34
TSP	-0.046	0.078	-0.59	0.067	0.056	1.20
Heating days	-0.053	0.041	-1.29	-0.068	0.030	-2.25
Cooling days	-0.088	0.056	-1.56	-0.198	0.041	-4.79
Precipitation	-0.208	0.046	-4.51	-0.049	0.029	-1.67
Windspeed	-0.137	0.089	-1.55	-0.139	0.062	-2.25
Humidity	0.242	0.132	1.83	0.071	0.096	0.74
Sunshine	0.811	0.209	3.89	0.848	0.141	6.00
Commute time	0.186	0.078	2.38	0.235	0.051	4.64
T-P ratio	0.243	0.135	1.80	0.086	0.099	0.87
Intergov rev	-0.019	0.052	-0.36	-0.044	0.035	-1.24
Local taxes	0.085	0.089	0.95	0.059	0.066	0.89
Property taxes	0.037	0.076	0.50	0.010	0.060	0.16
Time	0.621	0.098	6.36	0.611	0.072	8.51
Constant	5.110	2.034	2.51	4.003	1.405	2.85
	R-squared: 0.3747			R-squared: 0.6589		

* The bottom quartile has less than $11,300 in family income in 1990 dollars, and the top quartile has more than $34,400.

** A positive coefficient classifies that independent variable as an amenity.

Table 35
LOG-LINEAR REGRESSION WITH ALL CRIMES FOR WAGE EQUATION for the bottom and top quartiles in personal income

	Bottom Quartile*			Top Quartile*		
Hourly Wage	COEFF**	STD ERR	T-STAT	COEFF	STD ERR	T-STAT
Central city	0.032	0.008	3.76	0.007	0.006	1.23
COLI	0.410	0.126	3.26	0.113	0.096	1.19
Manufacturing	-0.151	0.105	-1.43	0.152	0.082	1.85
Unemployed	0.105	0.063	1.66	0.008	0.047	0.17
Murder	-0.001	0.017	-0.04	0.007	0.014	0.55
Rape	0.018	0.025	0.71	0.004	0.021	0.20
Robbery	0.021	0.018	1.22	0.005	0.014	0.34
Agg assault	-0.001	0.020	-0.07	0.011	0.015	0.78
Burglary	-0.060	0.040	-1.50	-0.103	0.032	-3.19
Larceny	-0.013	0.039	-0.34	0.023	0.030	0.76
Auto theft	-0.015	0.019	-0.79	0.001	0.015	0.08
Coastline	-0.001	0.017	-0.04	0.036	0.013	2.74
Pop density	-0.006	0.011	-0.52	-0.006	0.009	-0.61
Superfund	0.008	0.009	0.81	0.017	0.007	2.28
TSP	-0.047	0.039	-1.21	0.028	0.031	0.91
Heating days	0.002	0.024	0.08	-0.029	0.021	-1.39
Cooling days	-0.055	0.030	-1.79	-0.035	0.024	-1.47
Precipitation	-0.035	0.030	-1.17	0.057	0.021	2.72
Windspeed	-0.052	0.049	-1.07	-0.014	0.039	-0.35
Humidity	-0.065	0.064	-1.02	-0.031	0.052	-0.59
Sunshine	0.202	0.118	1.71	0.293	0.085	3.45
Commute time	0.127	0.049	2.59	-0.013	0.036	-0.37
T-P ratio	-0.076	0.069	-1.10	0.070	0.050	1.39
Intergov rev	-0.003	0.022	-0.14	-0.032	0.018	-1.79
Local taxes	0.021	0.039	0.55	0.048	0.032	1.51
Property taxes	-0.012	0.036	-0.32	-0.016	0.030	-0.54
Time	0.451	0.039	11.67	0.508	0.030	16.78
Constant	-0.541	0.903	-0.60	0.288	0.748	0.39
	R-squared: 0.3077			R-squared: 0.4683		

* The bottom quartile has less than $12,000 in personal income in 1990 dollars, and the top quartile has more than $34,000.

** A negative coefficient classifies that independent variable as an amenity.

Table 36
SIGN AND SIGNIFICANCE OF CRIME VARIABLES

	Log-linear Index crimes			**Semi-log Index crimes**			**Alternate Log-linear Index crimes**			**Alternate Semi-log Index crimes**		
Crime Variables	Rent eq	Wage eq	Total	Rent eq	Wage eq	Total	Rent eq	Wage eq	Total	Rent eq	Wage eq	Total
Violent crimes	Y*	N	N	N	Y	Y	N	Y	Y	N*	Y*	Y
Property crimes	Y*	N*	N	Y	N	N	N	N	N	N*	N	N
	All crimes			**All crimes**			**All crimes**			**All crimes**		
Murder	N*	N	N	N	Y	Y	N*	Y	Y	N*	Y	N
Rape	N*	Y	Y	N*	Y	Y	Y*	N	Y	N	Y	Y
Robbery	N*	Y*	Y	N*	Y*	Y	N*	Y*	Y	N*	Y*	Y
Aggravated assault	Y*	N*	N	Y*	N	N	Y*	N	N	Y	N	N
Burglary	Y*	N*	N	Y*	N*	N	Y*	N*	N	Y*	N*	N
Larceny	N*	Y*	Y	N*	Y	Y	N*	Y*	Y	N*	Y*	Y
Auto theft	Y*	N*	N	Y	N	N	Y*	N*	N	N*	N	N

* These variables are significant at the five percent level in the regressions.

** A "Y" indicates that the variable was correctly classified as a disamenity; a "N" indicates that the variable was labeled as an amenity.

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