Evidence of the Effects of Water Quality on Residential Land Prices[1]

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We use hedonic techniques to show that water quality has a significant effect on property values along the Chesapeake Bay. We calculate the potential benefits from an illustrative (but limited) water quality improvement, and we calculate an upper bound to the benefits from a more widespread improvement. Many environmental hedonic studies have almost entirely ignored the potential for omitted variables bias—the possibility that pollution sources, in addition to emitting undesirable substances, are likely to be unpleasant neighbors. We discuss the implications of this oversight, and we provide an application that addresses this potential problem. © 2000 Academic Press

Key Words: water quality; hedonic models; residential land prices.

1. INTRODUCTION

The absence of hedonic studies dealing with water quality in the environmental economics literature is striking. Despite a national concern for the health of waterways, and despite substantial public and private spending on water pollution abatement,[3] only five published studies in the last three decades have attempted to link water quality to waterfront property.[4] And yet a recent meta-analysis of air quality hedonic studies by Smith and Huang [33, 34] draws on data from over 25 papers. The paucity of water quality hedonic studies is particularly surprising when one considers that waterfront homeowners, by choosing to enter this high-priced

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[3]The Bureau of Economic Analysis estimates that total public and private water pollution abatement and control expenditures in the U.S. amounted to $42.384 billion in 1994 (the most recent year for which estimates are available)—13% more than air pollution abatement and control expenditures (Vogan [37]).

[4]David [13] explains variation in lakefront property values in Wisconsin using qualitative ratings of water quality; Epp and Al-Ani [16] examine the relationship between property values and pH levels in Pennsylvania streams; Steinnes [35] links water clarity at remote Minnesota lakes to property value assessments; Feenberg and Mills [17] build on Harrison and Rubenfeld's [19] early hedonic study of air pollution in Boston by introducing a measure of water quality ("oil" concentration and clarity) at nearby beaches; and Mendelsohn et al. [25] use panel data techniques to investigate the impact on property values of PCB contamination in New Bedford Harbor, Massachusetts.

market, have essentially self-selected for an interest in water related activities.[5] In contrast, there is no reason to expect that the homeowners included in an air quality hedonic study would have any unusually strong desire for clean air.

One explanation may lie with the *measures* of water quality commonly used by natural scientists. In contrast to particulate matter, which is frequently used to measure air quality, many water quality indices measure pollutants that are impossible for homeowners to observe or that do not directly impair the enjoyment the individual derives from his waterfront home. Dissolved oxygen, nitrogen, and phosphorous are three commonly used measures of water quality, yet substantial variations in any of these, while measurable with scientific equipment, will be unobservable to the eye. Only when high nutrient concentrations combine with other factors to cause algal blooms or fish kills will waterfront homeowners begin to notice. On the other hand, variations in water clarity (as measured by secchi depth or total suspended solids) are likely to be noticed by owners of waterfront homes. However, the benefits of improvements in water clarity have ambiguous ecological merit: mountain lakes plagued by acid rain can be crystal clear, yet completely sterile. Contamination from toxics such as PCBs and heavy metals naturally concerns waterfront homeowners, but because these substances tend to be trapped quickly in sediment layers, their impacts are often confined to industrial areas.

A second explanation for the scarcity of hedonic water quality studies involves the physical nature of water bodies and their relationship to housing markets. The use of hedonic analysis to capture the effect on price of improvements in environmental quality requires observations on sufficiently varying quality levels within the confines of a single housing market. Observations for an air quality analysis can be selected from two-dimensional space, but water quality studies are restricted to a one-dimensional coastline. Thus, researchers are often faced with a difficult tradeoff. Properties located on a single lake, for example, might all be associated with the same housing market, but water quality might not vary sufficiently across the lake. On the other hand, extending either the geographic or temporal domain of the analysis to capture more variation in water quality could extend the study beyond what can legitimately be considered a single market.

This paper presents evidence of a phenomenon rarely supported in the literature —that water quality affects residential property values. We use a measure of water quality—fecal coliform bacteria—that has serious human health implications and for which detailed, spatially explicit information is widely available to the public. Our study benefits from a particularly fortuitous geographic arrangement: a highly irregular estuarine coastline that supports a lively market for waterfront homes and that exhibits considerable variation in water quality within a small area. We obtain estimates of willingness to pay for marginal improvements in water quality and for a discrete improvement that is confined to a small area. We also calculate an upper bound to willingness to pay for raising water quality to the state standard for all residential waterfront properties along the Anne Arundel County coastline. Although our analysis is limited somewhat by the well-known difficulties of estimating discrete welfare measures within the hedonic framework, we have nonetheless

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[5] In an analysis of willingness-to-pay for water-related residences, Feitelson [18] finds that "The only characteristic typical of all consumers of water-related residences is their affinity for water-related leisure activities."

found evidence that water quality matters to waterfront homeowners and that people are willing to pay more for it. This conclusion is particularly interesting in light of the U.S. EPA's current efforts toward establishing a new generation of microbiological water quality standards (U.S. EPA [36]).

The results are especially convincing because we have controlled for a potential econometric problem that could compromise any hedonic study aimed at documenting the price effect of a change in ambient environmental quality. This is the possibility that the emitters of pollution may themselves be disamenities. If emitters are undesirable features of the landscape—because of odor, unsightliness, or noise—then the effect on housing prices of environmental quality variation will be difficult to distinguish from the effect of variation in these aesthetic disamenities. Ignoring this possibility could lead to biased estimates of the environmental quality coefficient.

2. APPLICATION OF HEDONIC ANALYSIS TO ENVIRONMENTAL PROBLEMS

While hedonic models were estimated as early as Waugh's [38] study of asparagus, tomato, and cucumber prices, Rosen [31] was the first to formalize the theory underlying the market for heterogeneous goods. In the Rosen framework, the price of any unit of a quality-differentiated good is a function of the levels of the characteristics embodied in the good. This function is increasing in characteristics that are valued by individuals because buyers will bid up the price of units with more of a desirable attribute. The hedonic price function is really a locus of equilibrium prices and arises as a result of the interaction of buyers and sellers in the market for the heterogeneous good. With the possibility of an approximately continuous array of characteristics available in the market, consumers choose levels of all characteristics such that the marginal price of each equals the marginal rate of substitution between each characteristic and a composite good.

If the hedonic price function can be accurately estimated, then the slope of the function with respect to a characteristic, such as ambient environmental quality, evaluated at the individual's optimal choice, represents that individual's *marginal* willingness to pay for the characteristic. Policymakers are often called upon to evaluate projects involving *discrete* changes in environmental quality, however, and for such cases the limitations of hedonic estimation for welfare analysis are well known. If the discrete change in quality is confined to a small area, then the welfare effect is a windfall gain to landowners equal to the total change in predicted property values (Palmquist [28], Polinsky and Shavell [30]). But if the discrete change in quality affects a large area, the hedonic price function will shift, and the total change in predicted property values serves only as an upper bound for benefits (Bartik [2]).

Despite the limitations of hedonic techniques in calculating defensible welfare measures of discrete environmental changes, hedonic analyses continue to appear in the environmental economics literature, and for good reason. Even when marginal values are of little interest and bounds cannot be justified, hedonic analyses are useful if they provide empirical evidence that the price of a heterogeneous market good reflects the level of some environmental good embodied in it. Given the sometimes-elusive nature of environmental benefits, such information is

valuable in its own right. It provides evidence that people would be willing to pay more for higher environmental quality and suggests a pathway through which people are affected by changes in the environmental good.

However, a convincing argument about the significance of environmental quality will depend ultimately on solid empirical work, for hedonic applications are plagued with ambiguities. Choice of functional form is arbitrary, the definition of the extent of the market is problematic, and multicollinearity poses problems for the selection of explanatory variables. Potentially more serious—yet less frequently discussed—is the possibility that omitted variable bias may lead to a biased estimate of the environmental quality parameter.

The first problem is sometimes handled by employing a flexible functional form, although a functional form that is too general may not prove robust to small mis-specifications (see Cassel and Mendelsohn [8]; Cropper, Deck and McConnell [12]). A satisfactory approach to defining the boundaries of the housing market has proven equally elusive. The boundary chosen by the researcher will necessarily be somewhat arbitrary; past definitions have ranged from the entire United States to micro-neighborhoods within individual cities. Palmquist [28] argues that while efficiency loss may result from considering too small a market, including only a subset of the housing market may yield better results.

Multicollinearity poses another perplexing problem. While the hedonic literature tends to emphasize the potential for severe multicollinearity among structural characteristics, neighborhood variables are likely to be correlated as well. Where the sets of collinear explanatory variables are not themselves the object of interest, or where they are all proxies for the same exogenous effect, selecting a subset of these collinear variables does little harm to the intent of the regression. However, this is not always the case, and omitted variables can sometimes lead to a biased coefficient estimate for a critical variable in the model.

In environmental applications, for example, measures of the level of a pollutant will often be highly correlated over space with proximity to pollution emitters. If the emitters themselves are undesirable neighbors for reasons unrelated to air or water quality, and if variables representing proximity to these emitters are omitted from the regression, then a statistically significant parameter estimate for the pollutant measure will be insufficient evidence for concluding that people care about air or water quality and are willing to pay to improve it. In the remainder of the paper, we use the term "emitter effects" to represent all effects, other than the pollution itself, that are associated with proximity to emitters. Sometimes, as we find in our application, emitters of pollution are associated with amenities, but more often the emitter effects are nuisances such as noise, odors, or negative visual impacts. Where negative emitter effects dominate, their omission can bias the coefficient on the pollution measure in the negative direction, making it more likely that the null hypothesis of no effect will be rejected.

In an early comment on the validity of the hedonic approach to environmental valuation, Kenneth Small [32] writes

> I have entirely avoided in this comment the important question of whether the empirical difficulties, especially correlation between pollution and unmeasured neighborhood characteristics, are so overwhelming as to render the entire method useless.

Although Small may not be referring precisely to what we define as emitter effects, his "unmeasured neighborhood characteristics" would no doubt include them. Surprisingly, very few hedonic studies have addressed this problem—despite a strong potential for emitter effects in many environmental applications. For example, a coal-fired power plant will be a source of airborne particulates *and* a noisy and unsightly neighbor. High automobile usage can lead to high ozone levels *and* to problems with noise and congestion. Some researchers have included explanatory variables such as the distance to industrial or manufacturing areas (Harrison and Rubinfeld [19], Jackson [21]), but these studies fail to identify the specific sources of air pollution or control for proximity.

Only two studies that we have found explicitly mention the possibility that the sources of air pollution may affect property values directly via emitter effects. In a 1980 study of the relationship between neighborhood disamenities and housing prices, Li and Brown [23] find that a negative and significant coefficient on air pollution loses significance when neighborhood characteristics such as noise and aesthetics are included in their model. They write that

> ...since there is a high correlation between air pollution levels and micro-neighborhood characteristics, previous findings about the effect of air pollution may in fact measure closely associated factors such as congestion, noise pollution, and visual disorder.

Likewise, in investigating the effect of particulates on housing values, Diamond [14] writes that

> [there is] a possibility that the presence of high levels of pollution in the more distant suburbs is related to the presence of another disamenity such as a manufacturing area or highway interchange.

However, he fails to address these effects with a more complete model specification.

Water quality hedonic studies may also be subject to bias from emitter effects. For example, David's [13] early analysis of Wisconsin lakes explicitly mentions pulp and paper production as being partly responsible for poor water quality, but she does not test whether her water quality parameter may be capturing the odor and noise associated with nearby pulp and paper company operations. Likewise, the impact of coliform bacteria on house prices found by Brashares [5] could include an emitter effect from nearby sources.

That emitter effects can be significant is supported by a recent analysis of the effect of hog operations on residential property values. While hog operations are frequently cited as sources of groundwater nutrient pollution, Palmquist et al. [27] explicitly focus on the emitter effects associated with these operations. In their investigation of the impact of manure odors on property values, the authors find that property values decrease as additional hog operations are added to the neighborhood of a residential home. However, they are careful to point out that their hog variable captures *all* of the effects associated with living near such operations—potential groundwater pollution from nutrient leaching as well as odors from manure. Without data on groundwater nutrient concentrations, their estimate of the emitter effect due to odor may be biased away from zero, and the researchers freely admit this possibility.

The problem posed by emitter effects may seem hopeless. If ambient pollutant levels decline with distance from the emitter, then the level of pollution and the emitter effect will be highly correlated. Fortunately, natural phenomena such as coastline irregularities, biological and chemical processes, and random weather events will all introduce variation that reduces the dependence of environmental quality on distance from the emitter. The more complex these fate and transport processes, the less collinearity will exist between water quality and the emitter effects, and the greater the likelihood that the effect of water quality will be estimated with precision.

3. A WATER QUALITY HEDONIC ANALYSIS IN ANNE ARUNDEL COUNTY, MARYLAND

Maryland's Anne Arundel County, located on the western shore of the Chesapeake Bay, is especially well suited for a hedonic analysis of water quality. Within 40 miles of both Baltimore and Washington, DC, the number of waterfront properties in the county is substantial. These waterfront locations are valued for their boat access to the Chesapeake Bay, for *in situ* recreational (swimming, wildlife viewing, fishing, and boating) experiences, and for aesthetic reasons. The irregularity of the Anne Arundel coastline (which inhibits mixing), together with the multiplicity and geographic dispersion of sources of water pollution, produces considerable variation in water quality.

The data used in the analysis consist of sales of waterfront property in Anne Arundel County, Maryland, that occurred between July 1993 and August 1997. The dependent variable is the actual sales price adjusted to constant dollars using the CPI. Only private, arms-length transactions were included and only those occurring along navigable sections of tributaries to the main stem of the Chesapeake Bay. The observations come from the State of Maryland's Tax Assessment data base and are made available from the Maryland Office of Planning which provides geocoded locations for the centroids of every land parcel in the state.[6] Fig. 1 depicts the location of the centroids of these parcels.

3.1. *The Measure of Environmental Quality*

Natural scientists are primarily concerned with three major water quality issues in the Chesapeake Bay: high concentrations of nutrients, toxic contamination, and fecal coliform bacteria.[7] In this study, we focus on water quality as measured by fecal coliform counts. We make this choice for a number of reasons. First, this pollutant is very likely to matter to individuals who wish to use the water adjacent to their property for swimming and fishing. When levels are high, the water can be

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[6] The Maryland Office of Planning [24] currently produces Maryland Property View annually, a GIS product which maps the centroids of all parcels in the tax assessment data base. We matched the sales data, also supplied by the Office of Planning in conjunction with the Maryland Department of Assessments and Taxation, to this geocoded database and to GIS coverages of other land attributes.

[7] In addition, concern over the micro-organism Pfiesteria has arisen in the last few years. But, thus far, Pfiesteria outbreaks have been confined to the Eastern Shore of the Chesapeake Bay.
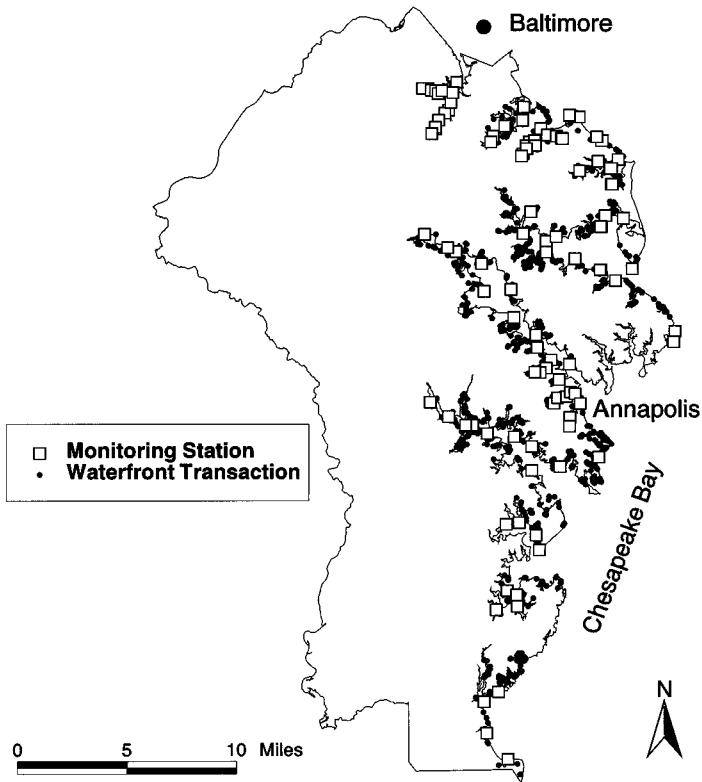
**FIG. 1.**   Monitoring stations and waterfront transactions. 1993–1997.

unsightly and may give off an unpleasant odor, and even moderate levels of fecal coliform pose a hazard to human health.[8]

Second, and just as important for our purposes, a mechanism exists by which information about fecal coliform levels is transmitted to market participants. Because fecal coliform is hazardous to water recreationalists, Anne Arundel County Department of Health collects weekly water samples from 104 stations long the shoreline of the Bay and analyzes these for fecal coliform counts. From Memorial Day to Labor Day, the department maintains a water quality hotline that describes weekly sampling results and waterway closings. When waterways are closed to swimmers, signs are posted by county officials and notices are printed in local newspapers. Finally, Department of Health officials report receiving several calls each month from realtors interested in water quality at particular locations.

In the hedonic model estimated in this paper, the water quality variable is derived from samples collected weekly at 104 monitoring stations along the Anne Arundel coastline.[9] The geographic distribution of these monitoring stations,

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[8]The State of Maryland recommends that beaches be closed if a logarithmic mean of 200 fecal coliform counts per 100 mL water is exceeded over a 30-day period.

[9]All stations were sampled during the months of April through September. Selected stations were also sampled during the winter months, but these winter observations were eliminated to maintain seasonal consistency across stations.
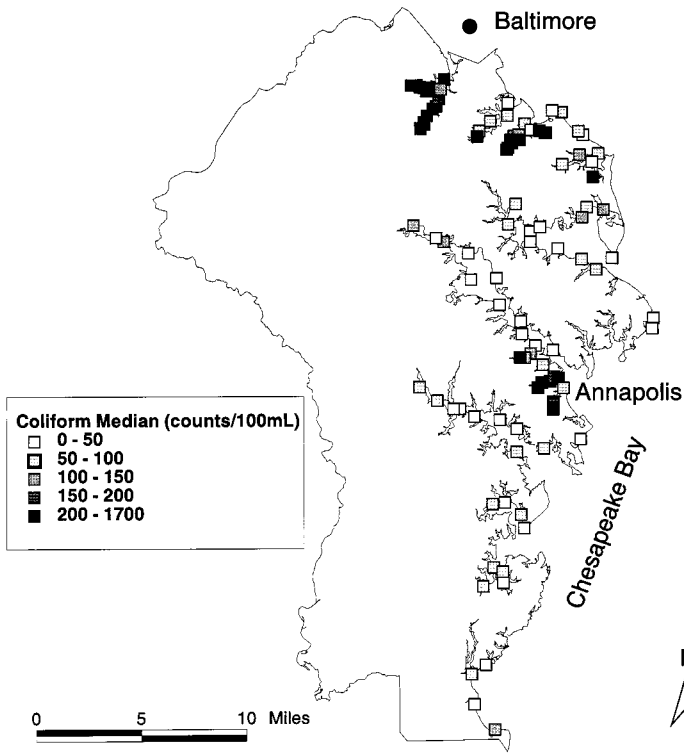
FIG. 2. Variation in fecal coliform.

together with ranges of the median fecal coliform values at these stations, are shown in Fig. 2. Although the monitoring stations are well distributed along the coast, some inlets and small bays are not monitored; sales transactions for parcels along these sections of coastline were dropped from the data resulting in a final sample size of 1183 transactions. For each waterfront property, we calculated an inverse distance-weighted average of fecal coliform counts (FECAL) based on data from the nearest three monitoring stations.[10] The index is constructed as

$$\text{FECAL} = \frac{1/d_1}{S}F_1 + \frac{1/d_2}{S}F_2 + \frac{1/d_3}{S}F_3,$$

where d_i is the distance in meters from the ith closest water quality monitoring station, F_i is the median fecal coliform value at the ith closest water quality monitoring station in the year of sale, and $S = 1/d_1 + 1/d_2 + 1/d_3$.

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[10] Concerned that our results may be sensitive to the manner in which this average is constructed, we estimated the hedonic using four different measures of FECAL. Each estimation included an index of water quality constructed with a different number of nearby water quality monitoring stations: the nearest station only, the nearest two stations, the nearest three stations, and the nearest four stations (where the set of potential nearest stations was constrained to the parcel's tributary). The results did not vary substantially with the alternative constructions of FECAL.

Although we focus on fecal coliform, it is important to consider whether other classes of water pollutants may be important to homeowners, and whether they are likely to be related in any way to coliform levels. Concentrations of toxic contaminants (such as PCBs and heavy metals) will concern waterfront property owners, but only a few localized areas of the Bay face serious toxic pollution problems: Baltimore Harbor, the Anacostia River near Washington D.C., and the Elizabeth River in Virginia.[11] The developed area of Anne Arundel County's coastline is characterized primarily by residential properties, beaches, and marinas; there is little heavy industry. The county has only two CERCLA Superfund sites, both of which are at least five miles from all waterfront residences.

The EPA's National Pollutant Discharge Elimination System (NPDES) database of major permitted point sources of water pollution includes three industrial sources of water pollution along the coast of Anne Arundel County. These plants may discharge pollutants that are known to local residents but for which we have no measures. In addition, the plants may be locally undesirable landscape features in their own right. To control for both these effects, we include as a measure of the proximity to these plants the inverse of the distance to the nearest non-sewage treatment NPDES site (DISTNPDES).

High nitrogen and phosphorous concentrations in the Chesapeake Bay (and the associated low levels of dissolved oxygen) have received considerable attention in recent years because of their ecosystem impacts.[12] The primary objective of the Chesapeake Bay Agreement, signed by three neighboring states and the District of Columbia, is to reduce concentrations of these nutrients. High nutrient levels can have adverse impacts on aquatic plants and animals, but variations in nitrogen, phosphorous, and dissolved oxygen concentrations are invisible to homeowners unless extremely high nutrient levels combine with the necessary chemical and biological conditions to cause algal blooms and/or fish kills. Although these events are aesthetically undesirable, they are not considered a danger to health, and public agencies do not make any effort to inform residents about concentrations of nutrients along the shoreline. In fact, no near-shore monitoring stations for nitrogen and phosphorous are maintained. Thus, residents are unlikely to be as aware of the spatial distribution of different levels of nutrients as they are of the spatial distribution of fecal coliform bacteria, and they will have less reason to be concerned about the former than the latter.

Fecal coliform concentrations may, however, be correlated with nutrient concentrations, because the two pollutants have several sources in common, and because inlets and streams that are poorly flushed will tend to concentrate both pollutant types. The correlation will not be perfect, because several major sources of nutrients (e.g., fertilizer run-off and airborne nitrates) are not sources of fecal coliform. Only to the extent that there is a correlation between the two *and* that

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[11] The Chesapeake Bay Program Executive Council [10] writes that "The revised Basinwide Toxics Reduction Strategy shall direct reduction and prevention actions toward regional areas with known toxic problems as well as areas where significant potential exists for toxic impacts on living resources and habitats. At this time the Elizabeth River, Baltimore Harbor, and the Anacostia River are designated as the initial Chesapeake Bay Regions of Concern."

[12] The Chesapeake Executive Council [9] writes that "The nutrients nitrogen and phosphorus are the most significant and widespread pollution threat to the Chesapeake Bay. These nutrients fuel algal blooms which cloud the water and ultimately result in low levels of the oxygen required by all the Bay's living resources."

individuals both know and care about nutrient levels, will our analysis capture more than a reaction to fecal coliform. If there is such an effect, the consequences of overstating the benefits of fecal coliform should not be serious, since, to the extent that these two types of pollution are sometimes produced in combination, policies aimed at the reduction of one will necessarily reduce the other.

3.2. Controlling for Emitter Effects

A single variable is used to measure the fecal coliform count in the water at site i, but separate variables are included to capture the emitter effects that might be associated with the various sources of this pollutant. The sources of fecal coliform in Anne Arundel County's marine environment are extremely diverse. In addition to natural sources, fecal coliform is introduced into marine waters via sewage treatment plants, leaking private septic fields, pet wastes, releases from septic holding tanks on private boats, and runoff from commercial animal facilities. Each source is unique with respect to the quantity and timing of emissions, the hydrological transport pathway, and the potential for causing emitter effects in surrounding neighborhoods. (Fig. 3 shows the locations or land use patterns associated with known emitters of fecal coliform.)
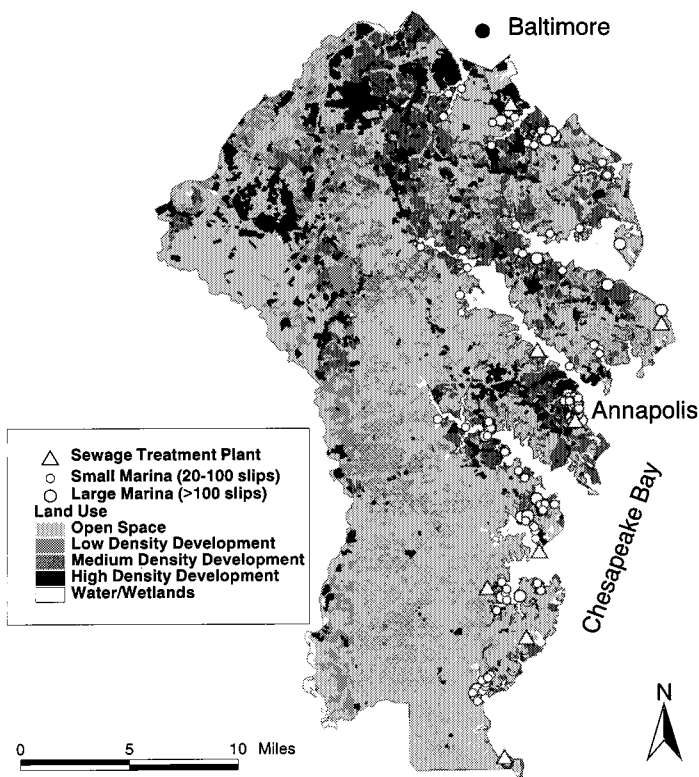

FIG. 3. Land uses and potential sources of fecal coliform.

The emitter effects associated with point sources are the easiest to control for. Sewage treatment plants are the most likely point sources of fecal coliform in Anne Arundel County. Because the topography is flat, and because the variable used to capture the emitter effect should dissipate quickly with distance, we use the inverse of the straight-line distance to the nearest plant (DISTSEWAGE). Inverse distance to the nearest sewage treatment plant is expected to have a negative coefficient in the hedonic regression if treatment plants are undesirable neighbors in their own right.

Since fecal coliform discharges from boats are likely to be concentrated around marinas and since marinas themselves may have a direct effect on property values, we also include proximity to marina locations as an explanatory variable. As with the two classes of NPDES sites, the specific explanatory variable is measured as the inverse distance to the nearest marina (DISTMARINA). However, in contrast to the NPDES sites, we have no *a priori* expectations for the sign of the DISTMARINA coefficient. It is an empirical question whether homeowners consider marinas to be either desirable or undesirable neighbors.

The nonpoint sources of fecal coliform are more difficult to capture convincingly, but equally likely to be associated with emitter effects. Runoff from areas that are densely developed and have high proportions of impervious surfaces often contain significant amounts of fecal coliform from pet and bird wastes. Agricultural areas and regions of low density residential development can contribute fecal coliform through septic field use and production of animal wastes. But the nature of the surrounding landscape is also likely to affect the value of a parcel directly (Bockstael and Bell [4]; Bell and Bockstael [3]; Irwin [20]). To capture the emitter effect associated with surrounding land uses, we include a set of landscape pattern variables. Taken together, these indices describe the nature of the surrounding landscape, which should have a direct effect on the value of a parcel.

Specifically, the landscape pattern variables are calculated for each parcel as the percent of the land within a three-quarter mile radius in each of four categories of land use:[13] (1) dense development (%HIDENS—commercial, manufacturing, and multifamily residential), (2) very low density land use (%LODENS—very low density residential, e.g., "farmettes" of 5 acres or more, and agriculture), (3) water (%WATER—open water and coastal wetlands), and (4) open space (%OPEN—natural vegetation either privately or publicly held). The omitted category of land use is medium density (from 0.2 to 8 dwelling units per acre) residential. The percent water measure is included to capture the fact that waterfront properties on peninsulas, with more water accessibility, are likely to be valued more highly (but also will be in areas with greater flushing). Our *a priori* expectations are that open space will be a positive amenity, but the desirability of very low density use and dense development are more ambiguous. Dense development may be associated with all the negative externalities of crowding, but will also signal the availability of services such as shopping, schools, hospitals, libraries, and cultural amenities.

Private septic fields may be associated with another type of emitter effect. Houses that depend on septic fields rather than public sewer service will be more likely to be located in areas where leaky septic fields are prevalent. But a house with a private septic field may or may not be preferred to one with public sewer

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[13] Land use data were obtained from the Maryland Office of Planning's digitized land use maps for 1990. This particular radius was chosen based on experience from other studies (e.g., Irwin [20]).

hook-up, independent of the amenities associated with the surrounding landscape. To control for this effect, we include a dummy variable for whether or not the house itself is on public sewer (PUBSEWER). We have no *a priori* expectation on the sign of this effect.

Feedlots and other concentrated animal operations may also be contributing to the fecal coliform levels through runoff from upstream activities. However, there are no such operations close enough to the coastline to cause emitter effects for these operations.

In general, we expect the emitter effects from point sources to be adequately reflected in line of sight distances and those from non-point sources by land use pattern variables. However, our direct measure of the amount of fecal coliform at any given site will be the realization of a function of the quantity of emissions from each of many sources and the distance the pollutant must travel *through the estuary* from each source. This function will be complicated by water currents, rainfall, winds, tides, and variations in water depth. Anne Arundel's extremely irregular coastline contributes to this complexity. In addition, the pathway of pollution from terrestrial sources will depend on topographical and geological factors that affect runoff patterns. The combination of simple emitter effect relationships and complex underlying ambient water quality functions will increase our chances of estimating with precision the effect of fecal coliform on property prices, if a significant effect does indeed exist.

3.3. *Housing and Neighborhood Data*

A number of additional explanatory variables are included in the hedonic regression to capture the factors that have typically been found to influence residential property prices. Because the data set contains few structural characteristics, we control for the value of house attributes by including the appraised value of the structure as an explanatory variable (VALSTRUCT). (In Anne Arundel County, the structure alone is given an appraised value—a value intended to be independent of the land and its neighborhood.) A potential problem with the approach is the possibility of bias introduced by the assessor or the assessment process. Although there is always the possibility that assessors may be influenced by the surroundings when providing an assessment of the structure value, appraisals are generally formula driven, where the formula includes several characteristics that we can not observe but that are observable to the assessor. In all cases appraisals were made within two years of the date of sale. We have adjusted the appraised value to constant dollars using the CPI.

In addition to the value of the structure, lot size (introduced nonlinearly as ACRES and ACRES squared) and commuting distance to nearby cities are hypothesized to affect sales price. Distances were measured using ARC/INFO software along road networks digitized in the Census Bureau's Tiger Line Files. Proximity to Annapolis (DISTANN), the state capital, is expected to be desirable, in part because of employment opportunities, but largely because the city offers amenities such as shopping, restaurants, and historic sites. Proximity to Baltimore (DISTBALT), the closest major city and largest employment center in the area, is also expected to be an important determinant of price. A variable equaling the cross-product of the distances to the two cities (ANNBALT) allows the marginal effect of proximity to Annapolis to vary with distance to Baltimore and vice versa.

Because a larger than normal proportion of waterfront property may be owned by retired individuals or held as second homes, we allow the effect of the distance to Baltimore to vary, depending on the percent of the population in the parcel's Census block group that was employed outside the county (%COMMUTE).

Washington, DC is also a major employment center in the region. However, preliminary regressions suggested that distance to Washington did not have a significant effect on property prices, leading us to omit this explanatory variable in the results reported in the next section. This may have occurred because the Anne Arundel coastline is at the limit of most people's assessment of a reasonable commute (approximately 1 hour each way); it may also have occurred because there is little variation in commuting distance to Washington, DC over our sample.

Two additional variables were included to correct for socio-demographic neighborhood effects—black population as a percent of total population in the Census block group and percent of owner occupied housing—but neither was found to be significant in any of our specifications so they are omitted from the regressions reported in the results.

4. ESTIMATION OF THE HEDONIC PRICE FUNCTION

Table I lists and defines the explanatory variables that are included in the hedonic regression. Because the hedonic price function is the locus of equilibrium points, there is little *a priori* information about its functional form. In simulation experiments, Cropper, Deck and McConnell [12] find that when variables are omitted or replaced by proxies, simpler forms—such as the linear, semi-log, double-log, and linear Box–Cox forms—perform better than more complex ones. Following their lead, we consider an array of relatively simple forms.[14] We specify the dependent variable both linearly and in logarithms, and we specify the distances and lot size measures both linearly and in logarithms. We do not transform the dummy variable that indicates access to public sewer service, nor do we transform the surrounding landscape measures which are already in percentages terms. This yields four specifications that we label "double-log," "semi-log," "inverse semi-log" and "linear."

Each of the four specifications is estimated with two alternative dependent variables: (a) *market transaction price minus assessed value of the structure* and (b) *market transaction price*. The former model reflects the additive nature of the value of structure and value of land that is implicit in the tax assessor's appraisal scheme. Under this assumption, the assessed value of the structure can be subtracted from the market transaction price to yield a "residual" land price, which we then attempt to explain. However, we cannot be certain that prices determined by the housing market actually embody this additive structure, so we also estimate all four specifications with *[market transaction price]* as the dependent variable. In this set of specifications, the assessed value of the structure is included as an explanatory variable—linearly in the "semi-log" and "linear" specifications and in logarithmic form in the "double log" and "inverse semi-log" specifications.

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[14] However, we do not estimate a linear Box–Cox model, for the non-linear parameters in this flexible form make the estimation of a spatial error model extremely difficult.

TABLE I

Variables and Descriptive Statistics

Variable	Description	Units	Min	Max	Mean	Std. Dev.
PRICE	Market price	$(1,000s)[a]	66.26	2081.98	378.54	263.01
VALSTRUCT	Assessed value of structure	$(1,000s)[a]	1.01	1187.29	125.29	103.55
ACRES	Lot size	acres	0.05	14.25	0.68	1.06
DISTBALT	Distance to Baltimore	miles	8.66	51.88	26.82	8.28
DISTANN	Distance to Annapolis	miles	0.31	28.98	12.27	7.04
%HIDENS	Percentage of land within 3/4 mile that is densely developed		0.00	0.41	0.04	0.07
%LODENS	Percentage of land within 3/4 mile that is developed at very low density		0.00	0.62	0.18	0.13
%WATER	Percentage of land within 3/4 mile that is water or wetlands		0.02	0.79	0.34	0.18
%OPEN	Percentage of land within 3/4 mile that is open space or forests		0.00	0.72	0.20	0.13
%COMMUTE	% of residents in census block group who commute out of county		0.08	0.55	0.29	0.10
PUBSEWER	= 1 if residence served by public water and sewer		0	1	0.48	0.50
DISTNPDES	Distance to nearest industrial NPDES site	miles	0.54	27.16	11.13	6.04
DISTMARINA	Distance to nearest marina with at least 20 boat slips	miles	0.00	3.04	0.83	0.67
DISTSEWAGE	Distance to nearest sewage treatment plant	miles	0.14	7.53	3.10	1.73
FECAL	Median fecal coliform concentration in year of sale[b]	counts per 100mL	10.48	1762.10	107.66	148.00

[a]1997 dollars.

[b]Inverse distance-weighted average of values at three nearest monitoring stations (see text for details).

4.1. *Results of the OLS Regressions*

The results of the eight specifications estimated using ordinary least squares are reported in (a) and (b) of Table II. When the dependent variable is measured in terms of transaction price and the assessed value of the structure is included as an explanatory variable, the assessed value is highly significant and the model explains approximately 70% of the variation in the dependent variable. As expected, when the dependent variable is measured as the residual land price *[market transaction price minus assessed value of structure]*, then the percent of explained variation declines considerably—to about 40%. Otherwise, the results across specifications are not dramatically different.

While our primary interest lies with the impact of water quality on property values and with the potential impact of emitter effects, reasonable results with respect to other variables support the validity of the exercise. In all specifications, price is found to increase but at a decreasing rate with lot size and to decrease with distance from both Annapolis and Baltimore. The decline in price with distance from Annapolis is less rapid for greater distances from Baltimore (and vice versa).

TABLE II

Parameter Estimates with (a) Market Price as Dependent Variable (in $1000s) and (b) Market Price Minus Value of Structure as Dependent Variable (in $1000s)[a]

Variable	Linear	Double-log	Semi-log	Inverse semi-log
		(a)		
Intercept	314.3462***	6.9587***	5.8256***	1077.8241**
	(7.1726)	(8.2533)	(50.0512)	(2.5647)
VALSTRUCT	1.7049***	0.4633***	0.0033***	185.7188***
	(41.4026)	(32.8698)	(29.7540)	(26.4339)
ACRES	84.3291***	0.1876***	0.2000***	112.6566***
	(9.9447)	(12.3270)	(8.8815)	(14.8492)
ACRES^2	−5.2583***	0.0121	−0.0148***	27.0001***
	(−5.7802)	(1.4662)	(−6.1383)	(6.5443)
DISTBALT	−7.7216***	−1.0196***	−0.0120***	−498.7033***
	(−4.5047)	(−4.0679)	(−2.6319)	(−3.9918)
DISTANN	−14.1511***	−1.0546***	−0.0369***	−426.6366**
	(−5.3605)	(−3.1244)	(−5.2570)	(−2.5360)
DISTBALT × DISTANN	0.4927***	0.2716***	0.0009***	118.7157**
	(5.0992)	(2.6694)	(3.5188)	(2.3408)
DISTBALT × %COMMUTE	−12.6627***	−0.1747***	−0.0330***	−54.4763***
	(−6.4048)	(−4.1389)	(−6.2815)	(−2.5891)
%HIDENS	361.0751***	0.4177**	0.4609**	324.4381***
	(4.5958)	(1.9992)	(2.2089)	(3.1150)
%LODENS	46.2638	0.1485	−0.0424	85.1355*
	(1.2598)	(1.6332)	(−0.4352)	(1.8785)
%WATER	262.1082***	0.6480***	0.5244***	296.6985***
	(8.0089)	(7.9240)	(6.0332)	(7.2793)
%OPEN	74.0476*	0.2927***	0.0932	92.9062*
	(1.8138)	(2.8627)	(0.8592)	(1.8232)
PUBSEWER	−1.6808	−0.0226	−0.0270	−4.6720
	(−0.1812)	(−1.0327)	(−1.0952)	(−0.4283)
Inv(DISTNPDES)	−135.6700***	−0.1359***	−0.5050***	−55.8996***
	(−4.4614)	(−3.4487)	(−6.2531)	(−2.8460)
Inv(DISTMARINA)	0.2612	0.0266***	0.0008	6.7999
	(1.1698)	(2.8683)	(1.3007)	(1.4684)
Inv(DISTSEWAGE)	5.4157	−0.0409**	−0.0072	6.5000
	(0.5819)	(−2.2054)	(−0.2911)	(0.7036)
FECAL	−0.0511*	−0.0002***	−0.0002**	−0.0803**
	(−1.8160)	(−2.6755)	(−2.4959)	(−2.1265)
N	1183	1183	1183	1183
R^2	0.7581	0.7333	0.6894	0.6362
X^2 (White's homoscedasticity test)	192.9132**	180.4017**	178.0194*	161.4148
F-statistic (joint significance of coefficients of emitter/ landscape variables)	12.9634***	12.2646***	8.9079***	10.9511***

This may be caused by the fact that the area between Annapolis and Baltimore is a less desirable neighborhood than the area at the same distance from Annapolis but to the south and the area at the same distance from Baltimore but to the west. The region midway between Baltimore and Annapolis is close to the regional airport and to the industrial districts associated with the wharves of south Baltimore.

Because much of the waterfront property is likely owned by retirees or held as summer homes, we include a variable equal to the distance to Baltimore multiplied

TABLE II—*Continued*

Variable	Linear	Double-log	Semi-log	Inverse semi-log
		(b)		
Intercept	445.8358***	11.9353***	6.3459***	1879.9018***
	(9.2410)	(7.8393)	(32.1476)	(4.9897)
VALSTRUCT	—	—	—	—
	—	—	—	—
ACRES	131.0783***	0.3264***	0.4111***	111.9448***
	(14.6024)	(12.2401)	(11.1937)	(16.9631)
ACRES^2	−8.4342***	0.0168	−0.0283***	20.9574***
	(−8.4696)	(1.1150)	(−6.9410)	(5.6196)
DISTBALT	−9.0215***	−1.9301***	−0.0330***	−478.6222***
	(−4.7116)	(−4.2308)	(−4.2096)	(−4.2397)
DISTANN	−17.0269***	−2.1308***	−0.0761***	−488.1501***
	(−5.7801)	(−3.4723)	(−6.3150)	(−3.2146)
DISTBALT × DISTANN	0.5333***	0.5548***	0.0019***	133.8013***
	(4.9382)	(2.9975)	(4.3636)	(2.9215)
DISTBALT × %COMMUTE	−13.2027***	−0.3026***	−0.0441***	−88.5834***
	(−5.9730)	(−3.9459)	(−4.8745)	(−4.6674)
%HIDENS	325.6553***	0.0963	0.7727**	170.5667*
	(3.7083)	(0.2540)	(2.1505)	(1.8174)
%LODENS	59.7778	0.1159	0.0366	37.0344
	(1.4562)	(0.7000)	(0.2177)	(0.9041)
%WATER	275.9341***	0.9002***	0.8767***	263.3281***
	(7.5428)	(6.0463)	(5.8569)	(7.1473)
%OPEN	20.5546	0.2909	0.1136	39.4547
	(0.4516)	(1.5690)	(0.6102)	(0.8599)
PUBSEWER	−0.8928	−0.0243	−0.0294	−5.3241
	(−0.0861)	(−0.6098)	(−0.6932)	(−0.5400)
Inv(DISTNPDES)	−149.4962***	−0.2063***	−0.8053***	−39.5786**
	(−4.3982)	(−2.8809)	(−5.7902)	(−2.2338)
Inv(DISTMARINA)	0.1445	0.0232	0.0015	0.0166
	(0.5791)	(1.3822)	(1.4495)	(0.0040)
Inv(DISTSEWAGE)	5.9401	−0.0667**	−0.0161	1.8330
	(0.5709)	(−1.9786)	(−0.3772)	(0.2199)
FECAL	−0.0656**	−0.0005***	−0.0004***	−0.0841**
	(−2.0843)	(−3.4568)	(−3.1506)	(−2.4645)
N	1183	1183	1183	1183
R^2	0.4014	0.4148	0.3899	0.4114
X^2 (White's homoscedasticity test)	176.5690***	136.5391	144.4853	163.0545**
F-statistic (joint significance of coefficients of emitter/ landscape variables)	13.3379***	8.6725***	8.2037***	12.2054***

Note. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.
[a]*t*-values in parentheses.

by the percent of the population in the Census block group that commutes to work outside the county. This variable allows the marginal value of proximity to Baltimore to vary with the number of residents in the Census block group that commute to the major employment center of Baltimore. The coefficient on this variable is significant and negative, as expected. The rate of decline in price with distance from Baltimore is higher for parcels in Census block groups with large commuter populations.

The variables reflecting surrounding land use patterns were jointly highly significant. As might be expected for waterfront properties, we found that the most important landscape pattern variable was related to water. An increase in the percent of water or wetlands surrounding the property had a significant positive effect on price in all specifications. The effect of dense development in the surrounding neighborhood was positive at the 5% significance level in all but two specifications, and at the 10% level in one additional specification. This suggests that the amenities from development outweigh the disamenities, at least in this particular market for waterfront homes. The remaining landscape pattern variables seemed to have little impact on price. In three specifications, increasing surrounding area in open space increased the value of the property significantly (at least at the 10% level), but in only one case did low density development have a significant effect on price.

Access to public sewer service did not have a significant effect on price in any of the models. This ambiguity is not at all surprising. There is no clear reason for the homeowner to prefer public sewer to private septic, or *vice versa*. In one case, homeowners pay periodic bills for public sewer service. In the other, they incur long-term septic field maintenance costs. Likewise, inverse distance to marinas had a significant effect on price in only one of the eight specifications, where the effect was positive. We did not have strong priors on the sign of this effect either, since marinas can be positive amenities with docking facilities, restaurants, etc., but they may also cause congestion and noise. The result may be further complicated by the likely correlation between marina location and water depth. Marinas tend to be located in areas with deep water, but deep water (or "draw") is an amenity valued by waterfront homeowners who desire boat access to the Bay.

The coefficient associated with inverse distance to sewage treatment plants was significantly different from zero in only two specifications. In contrast, the coefficient associated with distance to the industrial NPDES sites was consistently negative and significant.

4.2. *Interpreting the Fecal Coliform Coefficient and Emitter Effects*

The coefficient on fecal coliform count was negative and significant at the 5% level for seven of the specifications and at the 10% level for the remaining one, suggesting that even after controlling for potential direct emitter effects, higher levels of fecal coliform significantly depress property values. A change of 100 fecal coliform counts per 100 mL is estimated to produce about a 1.5% change in property prices. (For the models in which the dependent variable is not transformed into logarithms, this is the percent change evaluated at the mean price.)

The mean effect on the predicted price of a parcel for a 100 count change in fecal coliform ranged from a low of $5114 to a high of $9824 over the eight specifications we considered. A 100 counts per 100 mL change is a fairly substantial one, given that the mean fecal coliform reading is 103 counts per 100 mL, and given that state regulations require beach closings when 200 counts per 100 mL is exceeded. However, the range in fecal coliform readings along this area of the coastline is considerable: from 4 to 2300 counts per 100 mL.

Given our initial premise that the omission of direct emitter effects might bias the coefficient on the pollution variable, we explore this possibility in the context of the Anne Arundel County example. First, we test whether or not the emitter effects as a whole make a significant contribution to the explanatory power of the

regression. For all specifications, we find their joint contribution to the regression to be highly significant [see (a) and (b) of Table II].

Second, we examine the implications of omitting the emitter effect variables. We are particularly interested in seeing how omitting these variables affects the coefficient and standard error associated with the water quality variable. As we argued earlier, most environmental hedonic applications ignore emitter effects, and we expect this omission to bias estimates of the environmental quality coefficient in the negative direction. After omitting the landscape variables, the sewage treatment plant variable, the marina variable, and the sewer service dummy, all eight models are then re-estimated. The resulting estimated coefficients and t-statistics for the fecal coliform variable are reported in Table III along with the corresponding results extracted from (a) and (b) of Table II. In each case, the estimated coefficient on fecal coliform is larger in absolute value and the level of significance is greater when the direct emitter effect variables are omitted from the regression. In the specification where the fecal coliform coefficient is significantly different from zero only at the 10% level in the complete specification, it becomes significant at the 5% level when emitter effect variables are omitted.

4.3. *Econometric Problems*

Two statistical problems arise in the ordinary least squares regressions. Using White's test, the null hypothesis of homoscedasticity is rejected at the 5% level for four of the specifications—specifically the "double log" model with total market price as the dependent variable, the "inverse semi-log" model with residual land value as the dependent variable, and the "linear" model with both forms of the dependent variable. In addition, a series of diagnostic tests (Moran's I [26], Lagrangian Multiplier test [6], and Kelejian and Robinson test [22]) indicates the presence of spatial autocorrelation in all specifications. Spatial autocorrelation is far from surprising in a hedonic model, since omitted variables will generally be spatially correlated, but it is a problem that only recently has been taken into account in estimation (Can [7], Dubin [15], Bell and Bockstael [3]). Neither heteroscedasticity nor spatial autocorrelation biases the OLS coefficient estimates, but the estimates will be inefficient and—most troubling—the standard errors will be biased leading to inaccurate hypothesis tests.

Both because it is not easy to correct for heteroscedasticity and spatial autocorrelation simultaneously and because the simplest correction for heteroscedasticity is functional form transformation, we focus on the four specifications which do not exhibit heteroscedasticity in the OLS results and re-estimate these specifications correcting for spatial autocorrelation. A plausible model for spatial autocorrelation, and the one most commonly employed in the literature, is the one put forward by Whittle [39] and Cliff and Ord [11]. The spatial dependence among observations is assumed to take the form

$$y = X\beta + \varepsilon,$$

where ε is the stochastic term in the regression and takes the form

$$\varepsilon = W\varepsilon + u \quad \Rightarrow \quad \varepsilon = (I - W)^{-1}u$$

and u is assumed distributed independently and identically normal.

TABLE III

Fecal Coliform Coefficient with and without Emitter Variables[a]

	Dependent variable: market price minus value of structure				Dependent variable: market price			
	Linear	Double-log	Semi-log	Inverse semi-log	Linear	Double-log	Semi-log	Inverse semi-log
Fecal coliform coefficient with emitter/landscape variables included	−0.0656** (−2.0843)	−0.0005*** (−3.4568)	−0.0004*** (−3.1506)	−0.0841** (−2.4645)	−0.0511* (−1.8160)	−0.0002*** (−2.6755)	−0.0002** (−2.4959)	−0.0803** (−2.1265)
Fecal coliform coefficient with emitter/landscape variables omitted	−0.0776** (−2.5550)	−0.0007*** (−5.4880)	−0.0005*** (−4.099)	−0.1038*** (−3.2590)	−0.0584** (−2.1490)	−0.0003*** (−4.4970)	−0.0002*** (−3.3790)	−0.0840** (−2.3870)

Note. *, **, and *** denote that the estimated coefficient is significantly different from zero at the 0.10, 0.05, and 0.01 levels, respectively.
[a] t-values in parentheses.

In the above, W is a "spatial weights matrix" whose i, jth element, w_{ij}, is a normalized measure of the strength of association between the ith and jth residuals (see Anselin [1]). Given the micro-level nature of the observations, we define w_{ij} as the inverse of the distance between observations i and j. The maximum likelihood solution involves calculating the determinant of the $N \times N$ matrix, W, which is made easier the sparser is the W matrix. Using housing data in the Baltimore–Washington, DC area, Bell and Bockstael [3] found that the spatial autocorrelation effect disappears completely within a mile. We use this prior information and define w_{ij} as 0 if the distance between points i and j exceeds a mile.

Qualitative results do not change substantially after correcting for spatial autocorrelation in these four models. However, the coefficient associated with the density of development measure is not significant in two of the four specifications, and the coefficients associated with three of the distance measures are not significant in the inverse semi-log specification (Table IV). Spatial autocorrelation appears to introduce no consistent direction of bias in the standard errors of the estimated coefficient on fecal coliform, and the estimated coefficients remain significant in all specifications.

5. ESTIMATING THE BENEFITS OF IMPROVING WATER QUALITY

Having found a significant and defensible effect of fecal coliform levels on property values, we now use our results to value the benefits to property owners of water quality improvements. If the number of properties experiencing an improvement is small, the hedonic function itself can provide an approximate measure of welfare gains. Information about preferences is not necessary in this case, and the change in predicted property values resulting from a hypothetical change in fecal coliform will serve as an appropriate measure of benefits. The change in the predicted value of any particular waterfront property is not (necessarily) a measure of that property owner's valuation of the water quality improvement. It is a measure of the windfall gain in the value of his asset that he could recover by selling his property to an individual with a higher valuation for the amenity (Palmquist [27], Bartik [2]).

To illustrate the effect of a hypothetical, but reasonable, localized improvement in fecal coliform counts on a waterfront neighborhood, we considered the Saltworks Creek inlet along the Severn River northwest of Annapolis. Fecal coliform counts in this inlet are considerably elevated over the levels in the Severn River. Counts increase from about 50 counts per 100 mL at the mouth to 135 counts per 100 mL about a half mile into the inlet, and finally to a level of about 240 counts per 100 mL about a mile from the mouth. We chose a hypothetical level of 100 counts per 100 mL as the improved level in the middle and upper reaches of the inlet. Using this target level of fecal coliform, the resulting gains in property values for the 41 residential parcels that border the upper reaches of this inlet are calculated. Using the estimated parameter value from the inverse semi-log functional form after correction for spatial correlation, the projected increase in property values due to the hypothetical reduction in fecal coliform total approximately $230,000 (with a 95% confidence interval ranging from $105,000 to $353,000)

TABLE IV

Spatial Error Model[a]

Variable	Dependent Variable: Market Price Minus Value of Structure		Dependent Variable: Market Price	
	Double-log	Semi-log	Semi-log	Inverse semi-log
Intercept	11.6521***	6.2345***	5.7528***	1144.5700
	(5.3658)	(19.9471)	(31.0116)	(1.5539)
VALSTRUCT	—	—	0.0031***	172.3580***
	—	—	(28.5545)	(25.8538)
ACRES	0.3316***	0.4162***	0.2113***	113.6550***
	(12.3030)	(11.1745)	(9.3179)	(15.2761)
ACRES^2	0.0244	−0.0283***	−0.0155***	28.6263***
	(1.6245)	(−7.0045)	(−6.5158)	(7.1632)
DISTBALT	−1.8924***	−0.0319***	−0.0097	−536.2650**
	(−2.9003)	(−2.6546)	(−1.3643)	(−2.4225)
DISTANN	−1.9708**	−0.0707***	−0.0332***	−355.2450
	(−2.3153)	(−3.9121)	(−3.1200)	(−1.2568)
DISTBALT ×DISTANN	0.5120**	0.0017**	0.0007*	100.5600
	(1.9910)	(2.4995)	(1.7689)	(1.1759)
DISTBALT ×%COMMUTE	−0.2547***	−0.0323***	−0.0270***	−38.7333
	(−2.6696)	(−2.7995)	(−4.0039)	(−1.3618)
%HIDENS	0.1537	0.5670	0.2703	353.2960**
	(0.3168)	(1.1586)	(0.9433)	(2.3685)
%LODENS	0.1184	0.0690	−0.0304	104.5840
	(0.5347)	(0.2966)	(−0.2228)	(1.5020)
%WATER	0.9043***	0.8479***	0.4948***	312.5250***
	(4.7296)	(4.2508)	(4.2403)	(5.3368)
%OPEN	0.2608	0.0295	0.0471	94.5739
	(1.1705)	(0.1287)	(0.3508)	(1.4282)
PUBSEWER	0.0227	0.0205	−0.0012	9.8090
	(0.4868)	(0.4140)	(−0.0433)	(0.7343)
Inv(DISTNPDES)	−0.2280**	−0.6552***	−0.4142***	−83.2389***
	(−2.3804)	(−3.6732)	(−3.9699)	(−2.7072)
Inv(DISTMARINA)	0.0102	0.0005	0.0002	5.4508
	(0.5268)	(0.5603)	(0.3529)	(0.9820)
Inv(DISTSEWAGE)	−0.0661	−0.0223	−0.0134	6.8975
	(−1.4236)	(−0.4217)	(−0.4355)	(0.4519)
FECAL	−0.0005***	−0.0005***	−0.0002*	−0.1246***
	(−3.2948)	(−2.9895)	(−1.8537)	(−2.8487)
N	1183	1183	1183	1183
R^2	0.3915	0.3899	0.6894	0.6362

Note. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.
[a] *t*-values in parentheses.

for the 41 parcels.[15] This represents an increase amounting to about two percent of assessed value, since the aggregate full market assessed value of these 41 parcels before any change is in excess of $10 million.

[15] For this calculation, and for the calculation of the upper bound that follows, we use the results from the inverse semi-log form with market transaction price as the dependent variable, corrected for spatial autocorrelation. Of the four forms corrected for spatial autocorrelation, this was the only one that permitted us to estimate benefits without obtaining out-of-sample data for all of the explanatory variables.

If the number of affected properties is large, the hedonic price function may shift and the above approach to welfare estimation would be incorrect. However, Bartik [2] has shown that the property value increases predicted by the estimated hedonic function will provide an upper bound to the benefits of a widespread, non-marginal improvement in water quality. Making use of this result, we calculate an upper bound for the welfare gains to all residential waterfront property owners of a specific hypothetical improvement in water quality. The hypothetical improvement is one that would reduce fecal coliform counts at all waterfront properties to the state standard of 200 counts per 100 mL. Of the 6704 residential waterfront properties in Anne Arundel County, 494 have FECAL values (as calculated according to our previously defined measure) exceeding 200 counts per 100 mL. The upper bound estimate of the benefits of improving water quality at all 494 properties is $12.145 million (with a 95% confidence interval of $3.789 million to $20.501 million).

It is important to point out that these figures do not include all of the benefits of water quality improvements. For one thing, they leave out the benefits to owners of waterfront properties along tributaries without monitoring stations (approximately 750 parcels). They also ignore potential benefits to near-shore property owners, benefits to other recreational users of Anne Arundel County's waterways and beaches, as well as the benefits to individuals with nonuse values.

6. CONCLUSIONS

The paucity of hedonic water quality studies is startling, particularly in light of the widespread application of hedonic techniques to air pollution. This paper takes advantage of a unique geographical environment—a lively housing market along an estuary with large variations in water quality—to show that improvements in water quality can have a positive and significant effect on property values.

As with all empirical economics, a convincing story must lie behind the econometrics. Perhaps the most difficult problem in using behavioral models to value environmental policy changes is establishing with some degree of confidence the link between an objectively measurable environmental change and the behavior of individuals. A statistically significant relationship between behavior and an environmental measure does not demonstrate *causation*.

Hedonic studies of environmental quality are particularly vulnerable to omitted variables bias: the emitters of pollution often have direct effects on the value of nearby properties—for reasons completely unrelated to air or water quality. Very few hedonic studies have addressed this effect. We control for it by including several variables to proxy for the direct effect of the emitters, and find that the inclusion of these variables matters in our model. In all eight specifications, omitting emitter effect variables would have yielded larger negative coefficients on the pollutant measure and higher *t*-statistics. After accounting for omitted variable bias and after correcting for spatial autocorrelation, we still can conclude, but now with considerably more confidence, that waterfront homeowners have a positive willingness to pay for reductions in fecal coliform bacteria concentrations.

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