PAVEMENT CONDITION AND RESIDENTIAL PROPERTY VALUES: A SPATIAL HEDONIC PRICE MODEL FOR SOLANO COUNTY, CA

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ABSTRACT
Pavement management agencies spend a significant amount of public money every year to
maintain roads. This study uses hedonic regression to estimate the relationship between
pavement condition and residential property value in Solano County, California. We hypothesize
that pavement condition impacts property values in two ways: directly as an indicator of
neighborhood blight, and indirectly through its effect on traffic conditions and noise. Both
effects are expected to be in the same direction; as pavement condition declines, property values
are expected to decline as well. We developed regression models for the County as a whole and
for each city with the County. County-wide results indicate that there is no statistically
significant relationship between pavement condition and residential property value. However,
separate estimates for each city in the County showed a mixture of small positive, small
negative, and zero relationships. Because the results are both mixed and small in magnitude, we
cannot conclusively estimate the contribution of road pavement condition to the value of a home.
The one conclusion we can draw is that to the extent that road pavement condition does
contribute to home values, that contribution is probably small in dollar value. This suggests that
although there are other reasons to improve pavement condition, property value may not be one
of them.

Keywords: pavement condition index, residential property value, hedonic model, spatial
econometrics
INTRODUCTION
Road pavement condition relates directly to the generation of nuisances such as traffic noise and air pollution, which cause an unpleasant environment and health issues for neighborhoods adjacent to roads. Pavement management agencies spend a significant amount of public money every year to maintain roads and reduce the impacts of nuisances caused by pavement deterioration (4). Yet, U.S. roads continue to be in a state of disrepair, and there is substantial competition for these public dollars. If better roads are clearly associated with higher property values, this would provide evidence that the funds are materially contributing to community economic wellbeing. In this work, we investigate whether and how much road pavement condition influences the value of adjacent residential properties in cities and unincorporated areas of Solano County, California.

Many studies aim to estimate the impacts of environmental or nonmarket goods on human welfare. Multiple economic valuation methods have been developed to estimate these impacts, including contingent valuation models, travel cost models, and hedonic price models (2). In this study, we used the hedonic approach to estimate the influence of adjacent road pavement condition on residential property value. Hedonic price models use regression analysis to decompose the price of a good – such as a residential property – into the value of each of its characteristics. These characteristics include aspects such as home size and age, as well as characteristics of the surrounding area such as the pavement condition on the adjacent road. We measure pavement quality using the Pavement Condition Index (PCI). The PCI represents the structural and material integrity of a pavement in a numerical value (3). The PCI is expressed on a scale between 0 and 100, where a value of 100 represents the best possible condition (4).

There are two ways that pavement condition might impact property values: directly as an indicator of neighborhood blight, and indirectly through its effect on traffic conditions and noise, which in turn impacts property values. We expect that both effects are in the same direction; as pavement condition declines, we expect property values to decline as well. Solano County Transportation Authority was interested in whether or not proposed increased investments in road condition improvements would result in increased residential property values. We find, however, that in Solano County there was not a consistent detectable relationship between residential property values and pavement condition.

The paper proceeds as follows. First, we reflect on existing work in this area as it informs this study. Then, we describe the study area, data processing, and provide a detailed discussion of the PCI data itself. We then formulate our general regression model and present specific results for the selected models that can represent relationships between residential property values and PCI. We finish with a discussion and conclusions.

LITERATURE REVIEW
In this section, we review existing work that relates to this study. To the best of our knowledge, there is no existing peer-reviewed study that directly estimates the relationship between pavement condition and property values. Our work is the first. Thus, we review the closely related literature, including early hedonic studies that included presence of paved roads, the relationship between pavement condition and traffic noise, the impact of traffic volumes and associated noise on residential property values, and the impact of traffic emissions and noise on health.
Hedonic Price Models

Hedonic regression models estimate the economic value of nonmarket goods by separating the total value of the good (for example, real estate) – for which a market price is known – into the value of each of its characteristics, including “nonmarket” characteristics. Hedonic regression models typically use property sales prices as the dependent variable. Explanatory variables include characteristics of the properties (e.g., lot size, living area size, number of rooms, number of stories, age of building), the neighborhoods where they are located (e.g., median household income, population density, proximity of neighborhood park or open space), and the location of that neighborhood within a larger region (e.g., school district, distance to the central business district, proximity of transportation infrastructure).

Variation in the location of real property relative to environmental amenities (“benefits” i.e. local parks, schools, or transportation accessibility) or disamenities (“negative impacts” i.e. noise, crime, pollution, or neighborhood blight) provides the information needed to estimate the impact of those amenities and disamenities on the property’s value. The existing literature generally supports the hypothesis that neighborhood amenities – including high quality transportation infrastructure – have a positive influence on property values (e.g. 5,6,7,8,9), and that disamenities have a negative impact (e.g. 10,11,12). However, since there are no predetermined characteristics that are suitable for all hedonic models, knowledge of the local property markets and prior empirical studies are essential to define potentially important factors (2). Especially important is how the explanatory variables of interest (i.e. pavement condition index in this study) are measured.

Hedonic Studies that include the Presence of Paved Roads

Using data from the 1970’s and 1980’s, a number of prominent hedonic price model studies of urban property values included a variable indicating whether the road adjacent to a property was paved. Results based on the earlier data suggested a statistically significant and sizable effect (13), while studies using the more recent data did not (14,15). Our study follows this line of thinking directly, focused on how differences in the quality of paved roads adjacent to a property might affect value.

Relationship between Pavement Condition and Traffic Noise

Many studies have investigated the impact of traffic noise on property values (e.g. 5,10,16). Traffic noise closely relates to the pavement condition because one of the two main components of traffic noise is the friction between vehicle tires and the paved road surface (the other is vehicle powertrain operation) (17). This friction increases when pavements deteriorate, and there is substantial evidence that traffic noise increases with declining pavement condition (18,19,20).

The PCI provides information about pavement aging by including measures of distress, levels of severity, and distress density. That said, it is important to note that pavement-related traffic noise is also influenced by factors such as pavement materials (i.e. asphalt concrete, Portland cement concrete, or rubberized asphalt concrete), pavement texture types (i.e. longitudinal or transverse tine), traffic volume, vehicle types (i.e. truck or passenger car), and vehicle speed (17).

Impact of Traffic Emissions and Traffic Noise on Health

One mechanism for connecting pavement condition to community impacts and conditions is through health impacts. These impacts could be from traffic noise or vehicle emissions. Traffic
noise is connected with negative health outcomes, including increased incidence of hypertension and specific heart ailments (21). This problem increases with age and is inversely related to education and income. “Noise annoyance” (reported annoyance because of noise) occurs at traffic noise levels as low as 40 dBA (22) and has been proposed as an indicator for transportation planning (23). Because of potential health impacts, noise annoyance, and disruption of sleep, certain countries have developed traffic noise level thresholds for use in assessing existing impacts and in planning roadway/highway expansions in open space and residential areas (e.g., 50-55 dBA in Denmark (24,25)). It is likely that improved pavement condition could reduce both traffic noise and emissions, reducing the incidence of related health impacts. Degraded pavement condition may lead to reduced speeds, and/or increased incidence of deceleration and acceleration, both of which could increase vehicle emissions (26). Vehicle emissions are a primary source of air pollutants in urban and suburban areas (27), and these emissions can contribute to a wide range of health impacts, from cardiovascular problems to adverse birth outcomes and diminished male fertility (28). Indoor, residential air quality is related to distance from roads (29), which means that health impacts from degraded air quality will be greatest near roads with heavy or congested traffic.

### Relationship between Traffic Volumes and Residential Property Value

The hedonic modeling literature includes many studies of the relationship between traffic volumes and property values (e.g., 30,31,32). The studies we review find statistically significant and negative relationships between traffic volumes and single family residential property values in three distinct geographic contexts. Kawamura and Mahajan (30) find a small magnitude relationship between property values and total traffic, night traffic, and peak hour traffic. They emphasize the importance of testing and controlling for spatial autocorrelation in hedonic price models, which we do. Li and Saphores (31) focus on the impacts of truck traffic along highway links in Los Angeles, CA using a multiple distance band approach (i.e. within100m, 100-200m, and 200-400m) to identify impact zones. In contrast to Kawamura and Mahajan (30), their results indicate that truck traffic had a substantial impact on property values, while total traffic did not. Most recently, Larsen and Blair (32) estimated the difference in the effect of traffic on single family and multifamily residential housing values, finding that the effect of traffic was much larger – and in the opposite direction in some cases – for single family housing compared to multifamily housing.

### Relationship between Road Noise and Residential Property Value

The hedonic modeling literature also includes many studies of the traffic noise impact on property values (e.g., 5,33,34). In fact, traffic noise near the highway network was the main focus of many of the first transportation-related hedonic studies. Nelson (10) reviewed nine empirical hedonic studies focusing on the nuisance of traffic noise, finding that highway traffic noise has a negative impact on residential property values. Studies that include the traffic noise from arterial roads come to the same conclusion (e.g., 35). One recent study that married locally weighted regression techniques with hedonic models found that while the relationship between traffic noise and property values is generally negative, it varies substantially over space and time (34).

The existing literature provides estimates of the relationships between property values and presence of paved roads, traffic volumes, and road noise. Our study adds to the hedonic price
model literature with a focus on a new and related neighborhood characteristic – pavement quality.

STUDY AREA AND DATA
Solano County, CA is located in the northeastern part of San Francisco Bay Area and contains seven incorporated cities: Vallejo, Vacaville, Fairfield, Suisun City, Benicia, Dixon, and Rio Vista (see Fig. 1). Solano County had a population of 413,344 in 2010 (36) and 105,249 single family residential parcels in 2015 (37). Interstate highway 80 and an Amtrak rail line traverse the County.

To conduct this analysis, it was necessary to obtain sales price, assessor-based single family parcel and home characteristics, and nearby road pavement condition index (PCI) values for all included properties. Our data come from multiple sources including the Solano County Assessor's office (2015 parcel map, recent home sales), the Solano Transportation Authority (STA) (PCI from 2009-2015, and basic GIS layers), and ESRI web maps. For the dependent variable of residential property value, we used recent single family residential property sales values are available for the years between surveys based on a pavement deterioration model. Some of our home sales observations were missing structural information about the property. For some cases, the PCI values for the road segments adjacent to the property were unavailable. These observations were removed, leaving 19,608 observations available for modeling.

In addition to these characteristics, tract-level population density and median household income from the U.S. Census Bureau were included as control neighborhood characteristics in the analysis. For the locational characteristics, we used the “near” function in ArcGIS to calculate the Euclidean distance between each property and the closest Central Business District (CBD), highway exit, highway link, rail station, rail track, airport, water, park, and landfill. We assigned PCI to adjacent properties by first creating a buffer around each road, and then performing a spatial join with the property sales point data. Corner lots could have two streets adjoining them. In order to represent the street conditions most influential on the property, we attributed the street PCI value to the property that was closest to the centroid of the property. Indicator variables for year and city were created using attributes from the property sales data and city boundary polygon feature class, respectively.

It is possible that highway traffic noise was differentially attenuated at fine scales by purpose-built noise walls/barriers, or adjacent buildings. Because we lacked spatial data about these attenuating factors, we considered highway traffic noise to be a function of distance, which was represented by the locational variable “Within 320 m of Highway Center Line”. Properties were presumed to be exposed to local traffic noise, which would be related to PCI.

It is important to note that we used the home price index (HPI) for the San Francisco and San Jose area to adjust the sale price to be in constant 2015 real estate dollars. This controls for the substantial volatility in the real estate market during our study period of 2009 to 2015. Table 1 provides descriptive statistics for the main variables used in the analysis and Table 2 provides a percentage of observations for each city and year.
Table 1: Descriptive statistics of main variables (N = 19,608)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Property Sale Price</td>
<td>Constant US Dollars, Housing Price Index adjusted</td>
<td>$338,896</td>
<td>$153,794</td>
<td>$39,584</td>
<td>$1,562,303</td>
</tr>
</tbody>
</table>

Structural Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lot Area</td>
<td>Square Feet</td>
<td>6902</td>
<td>3366</td>
<td>650</td>
<td>194277</td>
</tr>
<tr>
<td>Living Area</td>
<td>Square Feet</td>
<td>1659</td>
<td>629</td>
<td>424</td>
<td>6051</td>
</tr>
<tr>
<td>Age</td>
<td>Years</td>
<td>34</td>
<td>22</td>
<td>0</td>
<td>149</td>
</tr>
<tr>
<td>Fireplace</td>
<td>0/1 (dummy)</td>
<td>0.83</td>
<td>0.38</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of Rooms</td>
<td></td>
<td>5.57</td>
<td>1.29</td>
<td>2</td>
<td>13</td>
</tr>
<tr>
<td>Two Stories</td>
<td>0/1 (dummy)</td>
<td>0.39</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Pool</td>
<td>0/1 (dummy)</td>
<td>0.07</td>
<td>0.25</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Garage Area</td>
<td>Square feet</td>
<td>440</td>
<td>150</td>
<td>0</td>
<td>4320</td>
</tr>
</tbody>
</table>

Neighborhood Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median income</td>
<td>US Dollars</td>
<td>$73,887</td>
<td>$23,699</td>
<td>$14,965</td>
<td>$145,625</td>
</tr>
<tr>
<td>Population density</td>
<td>People/Square Mile</td>
<td>4419</td>
<td>2974</td>
<td>36</td>
<td>12228</td>
</tr>
</tbody>
</table>
Substantial effort was put into thoroughly examining the PCI data to understand the relationship between PCI and the other variables used in the hedonic models, and to diagnose inconsistent PCI coefficients (i.e. sign and statistical significance changes) in the results of the selected regression models. The data included an estimated PCI value for road segments located immediately adjacent to the residential properties for each year from 2009 to 2015. These estimates were based on periodic field surveys of pavement condition. A pavement condition deterioration model was used to estimate PCI for each year between field surveys. The data also included the date and surveyed pavement condition value for the most recent PCI survey. In the remainder of this section, we highlight some data quality issues that we encountered when using these data.

First, surveyed PCI values may have measurement errors that could affect the results of hedonic regressions (2). An expert in grading the pavement condition of each road segment provided the PCI values in years when a road condition survey was done. The problem was that the same expert did not survey all of the roads in the County, leading to the possibility of inconsistency in surveyed PCI values. There has recently been a training program for pavement condition surveyors that aims to address this issue. However, the data we used spans the period both before and after the training program.

Second, we found large changes in some PCI values between estimated values in one year and surveyed values in the next. In the case of large PCI increases, it would make sense that road maintenance and/or capital improvement operations substantially improved the pavement.
condition, and then a new pavement survey confirmed it (e.g., an estimated PCI of 37 in 2013 and a surveyed PCI of 100 in 2014). However, changes in the opposite direction (e.g., an estimated PCI of 65 in 2010 and a surveyed PCI of 27 in 2011) are problematic because there was no reasonable explanation for them, and one or both of those PCI values are likely to be far from correct. If the estimated PCI is incorrect in these cases, it casts doubt on all estimated PCI values in the dataset. There are 891 cases in our data where PCI values decline sharply by more than 20 points from one year to the next, not including those cases where we know that the reason is a new PCI survey.

Because of uncertainty in consistency of estimated PCI values, we ran two regression models—one with the full dataset including both estimated and surveyed PCI (19,608 cases) and another that was restricted to the PCI data resulting from field surveys— which were marked only for the most recent field survey—or likely field surveys for previous years. To identify likely field surveys, we identified cases where year-to-year increases occurred, and marked them as likely additional survey years. We also marked year-to-year drops of more than 7 PCI points as likely additional survey years. Our sample size for homes sold in years with surveyed PCI included 5,121 cases.

HEDONIC PRICE MODEL

To select the best functional form for the hedonic regression model, we first examined scatter plots between the dependent and explanatory variables. These scatter plots tell us whether the relationships between the variables are best represented by a linear or nonlinear function, such as the natural log. We also checked for multicollinearity among our explanatory variables using the variance inflation factor (VIF) method. Based on these tests, we removed a number of collinear locational characteristics from the model (proximity to airports, landfill sites, and transit hubs).

We tested for spatial autocorrelation among observations. When residential property values exhibit spatial autocorrelation, a hedonic model will generate inconsistent estimates. The presence of spatial autocorrelation in the error term produces inefficient parameter estimates (38). We used standard spatial econometrics methods, testing for spatial autocorrelation in both the dependent variable and the error term. The test results confirmed that spatial autocorrelation only existed in the error term. Thus, we employed the spatial error model for the final regression analysis, which can control for spatial autocorrelation in the error term.

The functional form for our models is expressed in equation (1), which indicates our three types of independent variables and the spatial error specification. Many of our included independent variables are also log-transformed.

\[ \ln P_i = \alpha + \beta_1 S_i + \beta_2 N_i + \beta_3 L_i + \lambda W \varepsilon_i + \mu_i \]  

Where:

- \( P_i \) is the housing price index-adjusted sale price of property \( i \)
- \( \alpha \) is a constant
- \( S_i \) are structural characteristics for property \( i \)
- \( N_i \) are neighborhood characteristics for property \( i \)
- \( L_i \) are locational characteristics for property \( i \)
- \( \beta_1, \beta_2, \beta_3 \) represent the coefficients of \( S_i, N_i, \) and \( L_i \) respectively
- \( \lambda \) is the coefficient of the spatially correlated error term
- \( W \) is the standardized spatial weights mxm matrix with zero diagonal terms that assigns
the potential spatial correlation

\[ \varepsilon_i \text{ is spatial autoregressive error term for property } i \]

\[ W\varepsilon_i \text{ is the spatially lagged error term, and} \]

\[ \mu_i \text{ is independent but heteroskedastically distributed error term for property } i \]

RESULTS

Our overarching result is that we do not find a consistent relationship between pavement condition and residential property values in Solano County between 2009 and 2015. Here, we provide details of our econometric model results, first for a model estimated using data from the entire county, and then for models based on subsets of that data. The specific data subsets we present here are the subset of properties for which the adjacent road had a surveyed (vs. estimated) PCI value, and subsets for each incorporated city in the county.

In addition to the model results detailed in this paper, we investigated a wide range of alternative statistical model structures. Separate estimates for the home sale period from 2009-2011 and 2012-2015 provide varying results – a small positive relationship between PCI and sales prices for the earlier period and a small negative relationship for the later period. Estimates for high- and low-price subsamples of homes provide similar results. Estimating the model using data levels rather than natural logarithms did not change the results.

However, inclusion or exclusion in the analysis of certain other home and neighborhood characteristics that are correlated with pavement condition – including age of home and being adjacent to an arterial road – does influence the results. To avoid omitted variable bias, the results presented here are based on analyses that include as many relevant home and neighborhood characteristics as possible.

All Properties

Initial regression analysis was performed using StataSE 12 for Windows to determine the best model, and GeoDaSpace was used for the final regressions, correcting for spatial dependence. Lagrange Multiplier tests for spatial dependence in the dependent variable and in the error term confirmed spatial dependence only in the error term. In addition, a Koenker-Bassett test confirmed spatial heterogeneity in the data. Thus, we applied a spatial error model with heterogeneity option. Table 3 shows the coefficients, standard errors, z statistics, and significance for this model. The resulting model fit is fairly strong with a Pseudo $R^2$ of 0.79.

The structural explanatory variables are all statistically significant and their coefficient signs are as expected. For instance, number of stories and age of house are negatively related to the price, while other structural variables such as home square footage, lot size, number of rooms, presence of a fireplace, presence of a pool, and square footage of garage are all positively related to price.

For neighborhood variables, median household income is positively associated with property value, while population density is negatively associated with property value. The signs of both estimated coefficients are as expected.

The locational variables are also statistically significant, and most coefficients have the expected signs. Locations farther from the central business district (CBD) or from highway exits, which represents the accessibility of jobs and transportation, are negatively associated with the property values. Being adjacent to an arterial road is negatively associated with property values. Unexpectedly, locations farther from parks are positively associated with property values.
The estimated coefficient of PCI, the variable of the greatest interest, is both statistically insignificant and extremely small. This estimate – if it were statistically significant – would suggest that a 10 point increase in PCI would result in a $300 increase in value for the median-valued home in our dataset. This means that using the full dataset from Solano County, we cannot detect a relationship between residential property values and the pavement condition adjacent to the home. This initial null result led us to explore alternative ways to look at the data.

**Table 3: Estimation results, All properties (N = 19,608)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std. Err</th>
<th>z-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Living Area)</td>
<td>0.6074</td>
<td>0.0112</td>
<td>54.184</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Lot Area)</td>
<td>0.1008</td>
<td>0.0059</td>
<td>16.945</td>
<td>0.00</td>
</tr>
<tr>
<td>Number of Rooms</td>
<td>0.0148</td>
<td>0.0024</td>
<td>6.256</td>
<td>0.00</td>
</tr>
<tr>
<td>Two Stories</td>
<td>-0.0222</td>
<td>0.0044</td>
<td>-5.020</td>
<td>0.00</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0037</td>
<td>0.0002</td>
<td>-21.023</td>
<td>0.00</td>
</tr>
<tr>
<td>Fireplace</td>
<td>0.0611</td>
<td>0.0053</td>
<td>11.639</td>
<td>0.00</td>
</tr>
<tr>
<td>Pool</td>
<td>0.0617</td>
<td>0.0056</td>
<td>10.970</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Garage Area)</td>
<td>0.0113</td>
<td>0.0018</td>
<td>6.231</td>
<td>0.00</td>
</tr>
<tr>
<td><strong>Neighborhood variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Median Household Income)</td>
<td>0.1520</td>
<td>0.0084</td>
<td>18.013</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Population Density)</td>
<td>-0.0358</td>
<td>0.0015</td>
<td>-23.296</td>
<td>0.00</td>
</tr>
<tr>
<td>PCI</td>
<td>-0.0001</td>
<td>0.0001</td>
<td>-1.056</td>
<td>0.29</td>
</tr>
<tr>
<td><strong>Locational variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Distance to CBD)</td>
<td>-0.0188</td>
<td>0.0039</td>
<td>-4.815</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Distance to Highway Exit)</td>
<td>-0.0083</td>
<td>0.0033</td>
<td>-2.530</td>
<td>0.01</td>
</tr>
<tr>
<td>Arterial</td>
<td>-0.0584</td>
<td>0.0120</td>
<td>-4.883</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Distance to Park)</td>
<td>0.0129</td>
<td>0.0015</td>
<td>8.506</td>
<td>0.00</td>
</tr>
<tr>
<td>Within 320m of Highway Center Line</td>
<td>-0.0507</td>
<td>0.0064</td>
<td>-7.910</td>
<td>0.00</td>
</tr>
<tr>
<td>Constant</td>
<td>5.9830</td>
<td>0.1148</td>
<td>52.128</td>
<td>0.00</td>
</tr>
<tr>
<td>Lambda</td>
<td>0.0797</td>
<td>0.0110</td>
<td>7.240</td>
<td>0.00</td>
</tr>
<tr>
<td>PLUS CONTROLS FOR YEAR OF SALE AND CITY</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Properties with Surveyed PCI**

Because the estimated PCI may include errors due to the road deterioration prediction model over or underestimating the true pavement condition, we estimated our model using the subset of home sales that occurred in a year when PCI was surveyed on the road adjacent to the home. This subsample includes both home sales that occurred in the year when the PCI was most recently surveyed – as listed in the dataset – as well as home sales that occurred in a year for which we presume that the PCI must have been surveyed – based on the year-to-year patterns of estimated PCI values. Like the full sample, spatial autocorrelation for the error term was detected in this subsample, confirmed by the Lagrange Multiplier test. A Koenker-Bassett test again confirmed the presence of heterogeneity in this subsample. Thus, we again estimated a spatial
error model with the heterogeneity option using GeoDaSpace. Table 4 displays the results. The resulting model fit was strong with a Pseudo $R^2$ of 0.8. Overall, the results were not different from the All Property model. Structural variables were all statistically significant and all coefficients signs were as expected. For the neighborhood variables, median household income was positively associated with property value and highly significant, while population density was negatively associated with property value and highly significant. Signs of both coefficients were as expected. For the locational variables, some variables lost statistical significance compared to the All Property model. However, all signs were consistent with the All property model. The coefficient of PCI was again not statistically significant, from which we concluded that there was no detectable relationship between residential property values and pavement condition.

Table 4: Estimation results, Properties with surveyed PCI (N = 5,121)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std. Err</th>
<th>z-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Living Area)</td>
<td>0.6299</td>
<td>0.0220</td>
<td>28.579</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Lot Area)</td>
<td>0.0976</td>
<td>0.0115</td>
<td>8.498</td>
<td>0.00</td>
</tr>
<tr>
<td>Number of Rooms</td>
<td>0.0173</td>
<td>0.0048</td>
<td>3.626</td>
<td>0.00</td>
</tr>
<tr>
<td>Two Stories</td>
<td>-0.0177</td>
<td>0.0083</td>
<td>-2.138</td>
<td>0.03</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0042</td>
<td>0.0003</td>
<td>-12.306</td>
<td>0.00</td>
</tr>
<tr>
<td>Fireplace</td>
<td>0.0526</td>
<td>0.0096</td>
<td>5.488</td>
<td>0.00</td>
</tr>
<tr>
<td>Pool</td>
<td>0.0593</td>
<td>0.0111</td>
<td>5.334</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Garage Area)</td>
<td>0.0096</td>
<td>0.0037</td>
<td>2.594</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Neighborhood variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Median Household Income)</td>
<td>0.1001</td>
<td>0.0172</td>
<td>5.820</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Population Density)</td>
<td>-0.0403</td>
<td>0.0031</td>
<td>-13.088</td>
<td>0.00</td>
</tr>
<tr>
<td>PCI</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.552</td>
<td>0.58</td>
</tr>
<tr>
<td><strong>Locational variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Distance to CBD)</td>
<td>-0.0227</td>
<td>0.0079</td>
<td>-2.856</td>
<td>0.00</td>
</tr>
<tr>
<td>ln(Distance to Highway Exit)</td>
<td>0.0034</td>
<td>0.0066</td>
<td>0.508</td>
<td>0.61</td>
</tr>
<tr>
<td>Arterial</td>
<td>-0.0264</td>
<td>0.0211</td>
<td>-1.248</td>
<td>0.21</td>
</tr>
<tr>
<td>ln(Distance to Park)</td>
<td>0.0100</td>
<td>0.0030</td>
<td>3.337</td>
<td>0.00</td>
</tr>
<tr>
<td>Within 320m of Highway Center Line</td>
<td>-0.0266</td>
<td>0.0122</td>
<td>-2.187</td>
<td>0.03</td>
</tr>
<tr>
<td>(CONSTANT)</td>
<td>6.6041</td>
<td>0.2364</td>
<td>27.939</td>
<td>0.00</td>
</tr>
<tr>
<td>Lambda</td>
<td>0.1406</td>
<td>0.0178</td>
<td>7.884</td>
<td>0.00</td>
</tr>
<tr>
<td>PLUS CONTROLS FOR YEAR OF SALE AND CITY</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Pseudo $R^2$ 0.80

Properties in Each City

Table 5 shows a summary of the results for city-specific hedonic price models. Some cities such as Vallejo, Vacaville, Fairfield, Suisun City, and Rio Vista required the spatial error model with heterogeneity option, while other cities did not. The resulting model fits were generally strong, with goodness of fit statistics ranging from 0.64 to 0.86. The estimated relationship between PCI
and property value differed by city. Like the County-level models presented earlier, some city-level results from Vallejo, Vacaville, and Solano County were statistically insignificant. The relationships between PCI and price for Dixon and Rio Vista were negative and significant at the 0.01 and 0.05 level respectively, while Fairfield's was positive and highly significant at the 0.001 level. In Suisun City, the relationship between PCI and home values was positive and somewhat significant at the 0.1 level, while in Benicia the relationship between PCI and home values was negative and somewhat significant at the 0.1 level.

**Table 5:** Estimation results, Individual cities

<table>
<thead>
<tr>
<th>City</th>
<th>N = 19,608</th>
<th>Model</th>
<th>Adj- $R^2$ /Pseudo $R^2$</th>
<th>PCI Coef.</th>
<th>Std. Err</th>
<th>z-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vallejo</td>
<td>6,127</td>
<td>Spatial error/Het</td>
<td>0.70</td>
<td>-0.0002</td>
<td>0.0001</td>
<td>-1.568</td>
<td>0.12</td>
</tr>
<tr>
<td>Vacaville</td>
<td>5,165</td>
<td>Spatial error/Het</td>
<td>0.77</td>
<td>-0.0001</td>
<td>0.0002</td>
<td>-0.781</td>
<td>0.44</td>
</tr>
<tr>
<td>Fairfield</td>
<td>4,962</td>
<td>Spatial error/Het</td>
<td>0.86</td>
<td>0.0007</td>
<td>0.0002</td>
<td>3.766</td>
<td>0.00</td>
</tr>
<tr>
<td>Suisun City</td>
<td>1,645</td>
<td>Spatial error/Het</td>
<td>0.69</td>
<td>0.0003</td>
<td>0.0002</td>
<td>1.837</td>
<td>0.07</td>
</tr>
<tr>
<td>Benicia</td>
<td>971</td>
<td>OLS (no spatial autocorrelation)</td>
<td>0.75</td>
<td>-0.0004</td>
<td>0.0002</td>
<td>-1.689</td>
<td>0.09</td>
</tr>
<tr>
<td>Dixon</td>
<td>279</td>
<td>OLS (no spatial autocorrelation)</td>
<td>0.81</td>
<td>-0.0037</td>
<td>0.0007</td>
<td>-5.404</td>
<td>0.00</td>
</tr>
<tr>
<td>Rio Vista</td>
<td>243</td>
<td>Spatial error/Het</td>
<td>0.64</td>
<td>-0.0009</td>
<td>0.0004</td>
<td>-2.298</td>
<td>0.02</td>
</tr>
<tr>
<td>Solano County</td>
<td>216</td>
<td>OLS (no spatial autocorrelation)</td>
<td>0.85</td>
<td>0.0013</td>
<td>0.0009</td>
<td>1.444</td>
<td>0.15</td>
</tr>
</tbody>
</table>

**DISCUSSION AND CONCLUSION**

Pavement condition can deteriorate over time, leading to cracks, pits, and bumps. Re-paving is the primary municipal strategy to keep residential streets and arterials in adequate condition. One possible justification for increased public spending on road improvements is the increased residential and/or commercial property value resulting in treated areas. Theoretically, there are two ways that pavement condition might impact property values: directly as an indicator of neighborhood blight, and indirectly through its effect on traffic conditions and noise, which in turn impact property values. Both effects are expected to be in the same direction; as pavement condition declines, property values are expected to decline as well.

We estimated the relationship between pavement condition and residential property value in Solano County, California. To our knowledge, this is the first peer-reviewed study to estimate this relationship. Because substantial public resources are spent on maintaining pavement quality, understanding the relationship between pavement quality and property values could be important.

Our results were based on 19,608 single family home sales between 2009 and 2015. Because the period from 2009-2015 was one of substantial movement in the real estate market, the sale prices were adjusted using a Home Price Index developed for the San Francisco Bay Area. Detailed characteristics of these properties and their neighborhoods were assembled from the parcel-level County Assessor data and multiple GIS layers that provided information on location and neighborhood characteristics. The spatial data for road Pavement Condition Index
(PCI) at each address was provided by the Solano Transportation Authority. For some years, the roads were surveyed for pavement condition, and the PCI is a measured value. For other years, the PCI was estimated using a pavement condition deterioration model.

Based on several variations in the use of these data in models, we could detect no clear and robust relationship between pavement condition and residential property values. Using all of the residential property values available for the county, our best estimate for the relationship between pavement condition and sale prices was that the relationship was positive, but statistically insignificant and extraordinarily small. Separate estimates for the largest cities in the County were mixed. Estimates for subsamples for which PCI was surveyed directly vs. estimated produced equivalent results.

Because the results are both mixed and small in magnitude, we cannot conclusively estimate the contribution of road pavement condition to the value of a home. The one conclusion we can draw is that to the extent that road pavement condition does contribute to home values, that contribution is probably small in dollar value. This suggests that although there are other reasons to improve pavement condition (e.g., reduced noise), property value may not be one of them.

ACKNOWLEDGEMENTS

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