Hedonic Pricing Project Final Presentation Department of Geographical and Sustainability Sciences



Class Led by Dr. Heather Sander

KYLE BAUM TREVOR RILEY **EVAN CAYTON** 

JASON MCCURDY ERINN ROGOWSKI









# Economic Valuation of Protected Open Spaces in Iowa City, Iowa using Hedonic Pricing

Prepared by:

Kyle Baum, Evan Cayton, Jason McCurdy, Trevor Riley & Erinn Rogowski

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### Overview

- Background
- Project aim and hypotheses
- Methods
  - Study area
  - Data requirements and sources
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### Background

- Humans benefit from ecosystem services, but some are difficult to quantify or value economically.
- Hedonic pricing can be used to estimate the value of intangible services that have a direct effect on a market.
  - The price of a marketed good is related to its characteristics.
  - Often applied to variations in home prices that indicate the value of nearby environmental characteristics.
  - Values assessed by determining how the price a buyer is willing to pay for a certain characteristic changes as other characteristics change.



http://whatsthepointofaventura.com/ files/2012/10/Housing-Prices.jpg



http://www.euromotor.org/moodle/file.php/ 65/unit8Images/housePrices.gif

### Project Aim and Hypotheses

- The project seeks to quantify the economic value of the cultural ecosystem services afforded to local residents through the use of an hedonic pricing model.
- We predict that increasing proximity to protected open space will have a slight but positive effect on the value of single-family owner-occupied homes in Iowa City.
- Increasing proximity to spaces classified as 'natural areas' will have the most pronounced positive effect on the value of these properties.

### Methods – Study Area

- The Iowa City area, including a 500 meter buffer extending beyond city limits.
- Focus on:
  - All single-family owner-occupied dwellings sold between 2010 and 2015
  - All protected open spaces





### Methods – Data Requirements and Sources

- Shapefiles
  - Parcels City of Iowa City
  - Protected open space City of Iowa City
  - Elementary school district boundaries Iowa GIS Data Repository
  - Aerial imagery for park classification Iowa DNR
- Data
  - Sale data (acres, net building area, total rooms, bedrooms, bathrooms, garage area, age of home, sale price, date of sale) – City of Iowa City
  - Iowa Assessment Scores, grade 3 and 5 Greatschools.org

### Methods – Data Preprocessing

- Single-family owner-occupied parcels that sold between 2010 and 2015
- Sale data
  - Sale prices adjusted to 2015 dollars
  - Broken out by month, aggregated by season
- Euclidean distances
  - Parcels to nearby amenities
  - Parcels to nearest protected open space
    - Log transformed to reduce skew



### Methods – Data Preprocessing (cont'd)



Google Earth

- Classification of open spaces
  - Aerial imagery; broken into types
    - Based on landscape characteristics, identification of amenities
    - Small mixed use, large mixed use, and conservation/natural areas
- Linking test scores (grades 3 and 5) to elementary school districts
  - Iowa Assessment scores for math and reading; composite scores
  - Districts aggregated

### Methods – Analyses

- Ordinary Least Squares (OLS)
  - Linear regression that generates outputs relating a dependent variable to a set of explanatory variables.
  - Ability to test hypotheses and create predictions.
  - In ArcGIS, models spatial relationships and explains observed spatial factors.



http://resources.esri.com/help/9.3/arcgisengine/java/ gp\_toolref/spatial\_statistics\_tools/regression\_h.png

## Methods – Analyses (cont'd)

- Input feature class
  - Table featuring all parcel, neighborhood, and environmental variables
- Unique ID field
- Dependent variable
  - Sale price (adjusted to 2015 \$\$)
- Select explanatory variables and dummy variables
- Generate output report file and coefficient output table
- Run multiple times to find best model

Ordinary Least Squares		
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#### **OLS Diagnostics**

Input Features:	parcel_data_10Dec	Dependent Variable:	VALUE_2015
Number of Observations:	989	Akaike's Information Criterion (AICc) [d]:	26652.181597
Multiple R-Squared [d]:	0.318569	Adjusted R-Squared [d]:	0.309483
Joint F-Statistic [e]:	35.062446	Prob(>F), (13,975) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	322.697450	Prob(>chi-squared), (13) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	248.997389	Prob(>chi-squared), (13) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	5626.744279	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

#### Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-192486.0221	38078.552201	-5.054972	0.000001*	41165.167644	-4.675944	0.000005*	
ACRES	25705.663039	3507.451872	7.328871	0.000000*	9712.475351	2.646664	0.008255*	1.020320
BATHROOMS	21327.516061	8413.002997	2.535066	0.011388*	7477.082920	2.852385	0.004436*	2.571877
BD	16.748684	6.685595	2.505190	0.012390*	6.289993	2.662751	0.007874*	3.057282
SOLDSUM	45740.211384	11393.251066	4.014676	0.000072*	11384.690608	4.017695	0.000071*	1.027103
LINMANSHI	136666.96763	30541.874737	4.474741	0.000011*	34336.269772	3.980251	0.000082*	4.056003
BLDG_AREA	56.718605	12.378693	4.581954	0.000007*	14.903040	3.805841	0.000161*	1.911821
GARAGE	-46967.49493	15116.467894	-3.107042	0.001957*	17084.956165	-2.749056	0.006087*	1.079327
SMMX_PKD	13.631890	3.102508	4.393829	0.000016*	4.016806	3.393713	0.000733*	1.717704
LGMX_PKD	11.581328	4.340607	2.668135	0.007750*	4.146148	2.793274	0.005322*	2.294437
CONS_PKD	11.093410	2.535605	4.375055	0.000017*	2.576787	4.305134	0.000022*	1.903507
SMMX_PKAR	1.180760	0.224383	5.262242	0.000000*	0.193513	6.101720	0.000000*	1.411131
LGMX_PKAR	0.147003	0.074147	1.982577	0.047688*	0.066502	2.210513	0.027286*	3.353351
CONS_PKAR	0.060188	0.022226	2.708024	0.006885*	0.019147	3.143507	0.001734*	1.362965

### Results – Calculating Marginal Implicit Prices

Variable	Coef	StdError	t_Stat	Prob	Robust_SE	Robust_t	Robust_Pr	StdCoef
Intercept	-192486.0221630000	38078.55220100000	-5.05497218346	0.0000094588	41165.16764370000	-4.67594408526	0.00000478101	0.0000000000
ACRES	25705.66303900000	3507.45187180000	7.32887120867	0.0000000005	9712.47535135000	2.64666442994	0.00825511897	0.19571048548
BATHROOMS	21327.51606130000	8413.00299707000	2.53506578670	0.01138814231	7477.08291963000	2.85238458507	0.00443563408	0.10747887024
BD	16.74868388260	6.68559469594	2.50518983641	0.01238972087	6.28999280394	2.66275088139	0.00787400600	0.11580228200
SOLDSUM	45740.21138440000	11393.25106630000	4.01467597952	0.00007156775	11384.69060840000	4.01769472336	0.00007072214	0.10756384628
LINMANSHI	136666.96763600000	30541.87473750000	4.47474062449	0.00001110419	34336.26977160000	3.98025087013	0.00008192743	0.23824608052
BLDG_AREA	56.71860495960	12.37869289780	4.58195428451	0.00000709981	14.90304030690	3.80584121035	0.00016082299	0.16748776069
GARAGE	-46967.49493400000	15116.46789410000	-3.10704162262	0.00195746947	17084.95616460000	-2.74905563009	0.00608715405	-0.08533602398
SMMX_PKD	13.63188979460	3.10250818087	4.39382879912	0.00001551690	4.01680640884	3.39371341487	0.00073276587	0.15223904982
LGMX_PKD	11.58132759390	4.34060748747	2.66813519246	0.00775002825	4.14614843632	2.79327375076	0.00532196451	0.10684510886
CONS_PKD	11.09341026680	2.53560480468	4.37505491640	0.00001676321	2.57678653555	4.30513358935	0.00002232245	0.15957671440
SMMX_PKAR	1.18075964545	0.22438338088	5.26224197535	0.0000038494	0.19351258430	6.10172020466	0.0000000975	0.16525827737
LGMX_PKAR	0.14700308717	0.07414746187	1.98257746740	0.04768798691	0.06650179517	2.21051306651	0.02728592581	0.09597948894
CONS_PKAR	0.06018838292	0.02222594476	2.70802359920	0.00688501287	0.01914689246	3.14350660497	0.00173361483	0.08358021261

Variable	StdCoef	Mean Home Sale Price	250 m Closer to Park	MIP
SMMX_PKD	0.15223904982	\$236,662.00	-250	-\$144.12
LGMX PKD	0.10684510886	\$236,662.00	-250	-\$101.14
– CONS_PKD	0.15957671440	\$236,662.00	-250	-\$151.06

Variable	StdCoef	Mean Home Sale Price	Mean Park Area (m <sup>2</sup> )	MIP (m²)
SMMX PKAR	0.16525827737	\$236,662.00	37,849.20	\$1.03
– LGMX PKAR	0.09597948894	\$236.662.00	251.009.56	\$0.09
– CONS_PKAR	0.08358021261	\$236,662.00	363,416.69	\$0.05

### Discussion

- For every 250 meter interval a home is situated closer to a protected open space, home sale price <u>decreases</u> by:
  - \$144.12 small mixed-use park
  - \$101.14 large mixed-use park
  - \$151.06 conservation/natural area
- For every 500 square meter increase in each park type, home sale price increases by:
  - \$516.65 small mixed-use park
  - \$45.25 large mixed-use park
  - \$27.21 conservation/natural area

# Discussion (cont'd)

- While distance to the nearest type of each park may not factor into the home buying decision-making process, people may pay more to live near <u>larger</u> parks of each type, esp. small mixed-use parks that tend to be situated more closer to single family owner-occupied homes.
- Negative values may reflect certain attributes people associate with parks; values may be off as certain groups that are more likely to utilize parks were not included in the study (e.g. renters).
- Adjusted r-squared value = 0.309
  - Model explains only 31% of the variation in the dependent variable
  - Leaves 69% unexplained; poor model fit
    - Addressing heteroscedasticity and spatial autocorrelation will help improve this
  - Key explanatory variables may be missing from model; further study is needed to draw accurate conclusions

### Conclusions

- Homebuyers in the Iowa City area may place more emphasis on different variables (transportation, proximity to commercial areas and workplace).
- Larger parks in the area (e.g. Coralville Reservoir, Lake Macbride State Park, F.W. Kent Park) are not considered in this study.
- Inclusion of additional/different variables (views, other neighborhood characteristics) should be included in future studies to improve model fit.
- Hedonic pricing is a revealed preference method; stated preference methods (e.g. surveys) might better describe what residents value when it comes to utilizing protected open spaces.

### Acknowledgements

- Iowa Initiative for Sustainable Communities
- City of Iowa City
- Dr. Heather Sander

### Sources

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# Questions?