growth and change

Growth and Change DOI: 10.1111/grow.12147
Vol. 47 No. 4 (December 2016), pp. 461–480

Proximity to Natural Amenities: A Seemingly Unrelated Hedonic Regression Model with Spatial Durbin and Spatial Error Processes

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ABSTRACT The existing literature suggests that the presence of natural amenities, such as open spaces, can be highly valued and affect economic decisions about where people live and work. This article contributes to previous research by testing this hypothesis using a unique micro-level data set and by examining spatial variations in income levels and housing prices in the presence of natural amenities in a case study of Arizona. Proximity effects are estimated based on a geographic information system road network in which each variable represents the road mile distance from house *i* to its closest natural amenity within each category. Using a seemingly unrelated regression approach, spatial hedonic regressions of housing prices and income levels indicate that the total effect of various natural amenities calculated for the sample average income household and average home value, ranges from $2,382 (National Forests) to $1,560 (Wilderness areas). The presence of compensating differentials has policy relevance in considering the regional value of natural amenities. It also implies that valuation approaches such as the travel cost method may not reflect the full price of recreation site access, and may lead to underestimates of such values.

Introduction

The tradeoff between housing costs and commuting costs has been commonly cited as one of the main factors explaining residential location choices (Wu and Gopinath 2008). According to this classical urban economics model, high (low) income individuals will choose to live farther away (closer) from city centers as long as the income elasticity of demand for housing is greater than the income elasticity of commuting costs (Glaeser, Gyourko, and Saiz 2008; Sander and Testa 2009). However, as empirical evidence has raised questions about the validity of this theory (see Glaeser, Gyourko, and Saiz 2008; Wu 2010), recent literature has explored new factors to help better understand location decisions of households. A growing number of papers have looked at natural or environmental amenities as possible contributing determinants of residential location (e.g., Hand et al.

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Submitted June 2014; revised January 2015; accepted March 2015.
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2008a; Loomis and Richardson 2000; Schmidt and Courant 2006). These papers provide evidence that households may seek out areas that offer a so-called "second paycheck" derived from the value of the natural landscape (Niemi, Whitelaw, and Johnston 1999). The idea of a "second paycheck" underlines the combined link to both housing and labor market choices.

Forested lands and other protected areas may generate a variety of both market impacts (tourism effects on the local economy) and nonmarket effects (open space and recreation access, watershed and habitat protection, and other nonuse or passive use values). As one part of the total economic value (TEV) of these lands, proximity and access to natural amenities may be highly valued and affect decisions about where people live and work. The implicit values that people are willing to pay for access to these services may be observable in the housing and labor markets as compensating differentials (Hand et al. 2008b). In this case, it is hypothesized that a lower labor income (first paycheck), and possibly higher housing costs, may be compensated by a larger "second paycheck" (e.g., proximity or access to natural amenities).

Similar to earlier research by Hand et al. (2008b) for the Southwestern U.S., the objective of this article is to test this hypothesis by estimating spatial variations in wage and housing prices in the presence of forest and other natural amenities in a study of Arizona. Assuming that individuals select residential location partially based on proximity to natural amenities, this study follows Rosen (1974) and Roback's (1982) general equilibrium framework to explain wage and housing prices differentials for off-site benefits. This study uses a unique micro-level data set that matches housing and labor market outcomes to individual households, rather than relying on aggregate level Census data (as done in Hand et al. 2008b). Further, natural amenity effects are estimated based on a geographic information system (GIS) road network in which each variable represents the road mile distance from house i to its closest natural amenity within each category.

Accounting for two separate spatial processes, and using a seemingly unrelated regression (SUR) approach, spatial hedonic regressions of housing prices and income indicate that the average total annualized implicit prices for the sample average income household and average home value, ranges from $2,382 (National Forests) to $1,560 (Wilderness areas).

The presence of compensating differentials has implications for regional economic development, and particularly for policy decisions of whether to protect certain public lands. For example, results could be used to evaluate the magnitude and spatial distribution of natural amenity values associated with changes in public land preservation, such as Wilderness or National Monument designation. Also, results suggest where people choose to live and work is affected by access to natural amenities; thus, valuation approaches such as the travel cost method (see Randall 1994; Schmidt and Courant 2006), may not reflect the full price of recreation site access and lead to underestimates of the benefits.

Background. Because natural amenities generate multiple beneficial end uses, there have been competing allocation schemes for these resources. For example, this is seen in the policy debate about Wilderness Areas and Inventoried Roadless Areas (IRAs) that centers on the question of how these public lands should be managed. Wilderness Areas are Congressionally protected from various types of human intrusion, such as road construction under the 1964 Wilderness Act (USDA 1964, Pub.L. 88-577). Many input–output models predicted that prohibiting commercial activities (e.g., logging) would have prolonged negative impact on the economies of the affected areas (Schmidt and Courant 2006). However, the economic performance of such regions has been anything but negative and empirical evidence suggests that spending for outdoor recreation activities has not been significantly impacted by the recent great recession (Loomis and Keske 2012). The policy debate about IRAs centers on whether to manage these lands as Wilderness Areas (Aaron 2011; Voicu 2010). As

of today, a State petition rule allows each State to file IRAs petitions for wilderness consideration. While many of the protection-oriented petitions based their argument on the existence of both on-site and off-site benefits, the absence of explicit market prices poses a challenge for policy makers assessing the benefits and costs of protection.

This research provides estimates for a portion of the TEV of these amenities. For instance, there may also be on-site recreation values and passive values that are not captured in wage or housing prices. Loomis (1996) reviews evidence from various contingent valuation studies that passive use values may represent a significant percentage, and sometimes a majority proportion, of TEV associated with protected forest areas in the U.S. This suggests that off-site amenity values to residents, as measured here, might represent just one of several significant components of the TEV.

The empirical framework and the nature of the data used in this study offer the following contributions to the current literature. First, we estimate the effect on housing and labor markets of site-specific characteristics, such as forest areas, Wilderness Areas, national parks, superfund sites, and outstanding waters, based on a GIS road network analysis.[1] While a growing number of studies have looked at forest amenities to account for persistent differences in wages and housing prices, measurement of such variables have been limited to percentage of forest areas within a predefined administrative boundary or a straight line distance (Hand et al. 2008a; Schmidt and Courant 2006). These variables represent the road mile distance from house *i* to its closest natural amenity within each category. Second, this article addresses the possibility of spatially-dependent relationships in housing and labor markets by estimating spatial regression models. The underlying spatial relationships among observations were determined by applying Lagrange Multiplier (LM) tests for the coexistence of spatial lag and spatial error processes.

Lastly, this study uses micro-level data with fine-scale geographic data to mitigate the potential for geographic aggregation biases. It is common in many studies of the role of forest amenities (e.g., Hand et al. 2008b; Schmidt and Courant 2006) to use geographic data aggregated to political boundaries (such as counties, Census tracts and Public Use Microdata Areas). This creates the possibility of measurement errors due to geographic aggregation bias if empirical results depend on the spatial arrangement of zones or the scale used to estimate the econometric models (Doll, Morley, and Muller 2004).[2] The scale effect arises when the results found using the same data vary as the aggregation level of observation changes (Wrigley et al. 1996). The zone effect occurs when the administrative boundaries are arranged in a different way or zone boundaries are changed. The consequence of these effects is that results based on a particular aggregated administrative boundary may not be generalized to different spatial resolutions or scales. This is also known as ecological fallacy (Cao and Lam 1997). In this article, proximity to a natural amenity is measured based on individual house locations as opposed to an arbitrary defined administrative boundary centroid.

Hedonic Framework

This article uses hedonic theory to test the empirical question of whether natural amenities, such as open spaces and protected water bodies, are in fact amenities that significantly affect housing-price and wage differentials in Arizona. Hedonic price studies hypothesize that visual or proximal access to some set of environmental amenities and disamenities are capitalized into housing and labor markets. Such a bundle varies across a region depending on where the household lives and works, which gives rise to the hypothesis of compensating differentials in housing and labor markets.

A plausible approach to estimate the implicit marginal housing price of natural amenities is to apply a hedonic approach. This method decomposes the statistical variation in prices for a

heterogeneous good (e.g., residential real estate) to isolate the contribution of individual attributes or characteristics of the good (Taylor 2003). Following Freeman's (2003) theoretical hedonic price framework and using a vector notation, the price of a house depends on housing structural characteristics **S** (lot size, number of rooms, year built), neighborhood characteristics **N** (school quality, income level) and location-specific amenities **Q** (distance to a natural amenity), such that for a house i in location j:

$$P = P_{ij}(\mathbf{S}_i, \mathbf{N}_j, \mathbf{Q}_j) \tag{1}$$

where i refers to a specific house within neighborhood j. There is a wide consensus in the literature on these categories as explanatory variables for housing prices. Empirical evidence investigating the impact of various types of natural amenities and air quality in the housing market show a statistically significant correlation with house values (Greenstone and Gallagher 2008; Wu and Gopinath 2008; Hand et al. 2008b; Kim, Phipps, and Anselin 2003). In this application, the vector **Q** includes road mile distance to seven types of amenities: Wilderness areas (WILD), National Forest (FOREST) lands, Outstanding Waters (WATER), Congressionally-protected National Monuments (LNPMONU), unprotected National Monuments (LNUMONU), State parks (STPARKS), and city parks (CYPARKS).[3] Without assuming any particular form, such as a Box-Cox transformation or log-linear specification, the econometric equivalent of equation (1) is:

$$P_{ij} = \alpha_0 + \mathbf{S}_i\beta + \mathbf{N}_j\varphi + \mathbf{Q}_j\theta + \varepsilon_i, \tag{2}$$

where α, β, φ, and θ are the coefficient vectors to be estimated. The coefficient of interest represents the effect of, for instance, road mile distance to WILD on housing prices. The disturbance ε_i is assumed to be normally distributed, although its covariance matrix is of the general form Ω to account for heteroskedasticity and autocorrelation (i.e., off-diagonals are nonzero).

Building on Mincer's (1974) wage equation, annual household income is a function of the household's human capital characteristics **HC** (education level, race, employment status), neighborhood characteristics **N**, and location-specific amenities **Q**, such that:

$$\mathrm{HHINC}_{ij} = \gamma_0 + \mathbf{HC}_i\eta + \mathbf{N}_j\pi + \mathbf{Q}_j\delta + \mu_i, \tag{3}$$

where Υ is the self-reported annual income for respondent i in location j from the sample data. It is important to note that as the main focus of this study is the effect of natural amenities and not the prediction of wages per se; the correlation between income levels and natural amenities reported in this study does not have to necessarily change if wages were used instead. Moreover the i subscript represents household income and characteristics as opposed to a particular type of job (e.g., working conditions).

Spatial Econometrics Approach. The model specification in equations (2) and (3) has been widely used in applied hedonic studies. However, these equations do not address spatially-dependent relationships that emerge when using randomly distributed geographic data (Anselin 1988). In general, spatial dependence (or spatial autocorrelation) refers to the notion that what happens in one point in space relates to what occurs in other locations.[4] In many instances, this arises due to random specifications of geographic units, such as census tracts or county boundaries, which may not accurately reflect the extent to which the phenomenon in question behaves in space (Anselin 1988). Another reason is that regardless of whether data corresponds to individual spatial units or aggregated units, diffusion processes (e.g., spillover effects) result in spatial autocorrelation between

different spatial units depending on location and distance. In this sense, the presence of spatial autocorrelation is not limited to cases with data collected at an aggregate level but also to point data or individual-level observations (Anselin 1988), which is the case of this study.

Spillover effects may arise due to the actions and interactions among local jurisdictions that determine some local characteristics (e.g., parks and landfills) and fiscal conditions (e.g., property taxes and welfare payments). That is, jurisdictions may respond to decisions that influence quality of life made by other nearby jurisdictions through a strategic reaction function (Anselin 2002; Brueckner 2003; Brueckner and Saavedra 2001).[5] Decisions by local jurisdictions could also account for nearby characteristics of federally managed land. In the present case, the primary variables of interest are federally managed forest and Wilderness Areas; states and local jurisdictions have little influence over the distribution of such resources. However, other characteristics that may affect housing prices and household income (e.g., parks, environmental abatement, and tax rates) are likely determined by local jurisdictions and strategic interactions between jurisdictions. Spillover effects and resulting spatial dependence would in part reflect the equilibrium provision by local jurisdictions of location-specific amenities in response to the distribution of amenities provided by nearby federal lands and other local jurisdictions.

Econometrically, spatial dependence can result in nonspherical disturbances (i.e., the off-diagonal terms in the variance-covariance matrix of the disturbance vector are not all zero). In the context of this study and the housing price market, this could be driven by housing prices being spatially correlated (e.g., price of house *i* is a function of changes in the price of house *k*) or due to a general correlation of error terms.

Six different linear spatial econometric models have been identified in the literature for cross-section studies (Elhorst 2010). These models are: Manski model, Kelejian-Prucha model, spatial Durbin model, spatial Durbin error model, spatial lag model, and spatial error model (Elhorst 2010). Each of these models assumes different data generating processes (DGP).

A large number of studies have assumed either a spatial lag and/or a spatial error DGP. In the first case, the hypothesis is that housing prices are spatially related and therefore, a vector of house prices observed at other locations is included on the right hand side of the hedonic model. In the second case (spatial error model), spatial dependence is assumed to arise due to the omission of variables that are related in space. As a result, spatial dependence is introduced in the functional form of the error term. The corresponding estimation equations for each DGP are:

$$y_{m,ij} = \alpha_{m,0} + \rho_m W_1 y_{m,k} + X_{m,i}\beta_m + \mathbf{N}_{m,j}\varphi_m + \mathbf{Q}_{m,j}\theta_m + \varepsilon_{m,i}, \forall \quad i \neq k, \text{ and} \tag{4}$$

$$y_{m,ij} = \alpha_{m,0} + \mathbf{S}_{m,i}\beta_m + \mathbf{N}_{m,j}\varphi_m + \mathbf{Q}_{m,j}\theta_m + \varepsilon_{m,i} \tag{5}$$

$$\text{with } \varepsilon_{m,i} = \lambda_m W_2 \varepsilon_{m,k} + \xi_m,$$

where **y** is an *n* by 1 vector of response variables (e.g., home values, P, or household income, HHINC) for equation *m*, observation *i*, and neighborhood *j*.[6] ρ_m is the spatial lag autoregressive coefficient, λ_m is the spatial error autoregressive coefficient, and ξ_m is a zero mean vector of spherical disturbance. W_1 and W_2 are an *n by n* weight matrix that indicates how observational units are related in space. Both weight matrices have nonzero elements w_{ik} when observations *i* and *k* are defined as neighbors. The spatial lag coefficient (ρ_m) represents a weighted average effect of housing prices or income level in neighboring units (e.g., the effect that a change in the price [income] of [in] house *k* has on the price [income] of [in] house *i*).

There is also the possibility to include both a spatial lag of the response variable and a spatially autocorrelated error term in the same model if there is no a priori spatial specification in mind (Ham et al. 2015; Kelejian and Prucha 2004; Zhou and Kockelman 2009). While this specification appears to be more flexible than that of equations (4) or (5), it is does not allow for the possibility of including spatially lagged independent variables as the estimated parameters would then be unidentified (Manski 1993). In this case, LeSage and Pace (2009) recommends including the spatially lagged independent variables and excluding the spatially autocorrelated error term. The authors show that doing so will only cause a loss in efficiency as opposed to bias and inconsistent coefficients if explanatory lagged variables are ignored. As a result, a spatial Durbin model is proposed in the model identification process. In this case, the estimated equation becomes:

$$y_{m,ij}=\alpha_{m,0}+\rho_m W_1 y_{m,k}+X_{m,i}\beta_m+\mathbf{N}_{m,j}\varphi_m+\mathbf{Q}_{m,j}\theta_m+W\mathbf{S}_{m,i}\gamma_m+W\mathbf{N}_{m,j}\eta_m+W\mathbf{Q}_{m,j}\phi+\varepsilon_{m,i},\forall i\neq k \tag{6}$$

The authors show that the estimates from this model are unbiased even if the true DGP is a spatial lag or a spatial error model.[7] In this paper, we follow the "general to specific" specification process described in Elhorst (2010) to identify the most appropriate spatial empirical model for our dataset.

A recurring issue in these types of spatial models is the specification of the weight matrix (W). In the majority of the cases, this matrix is not endogenous to the model but predefined and arbitrary. The lack of consensus and evidence regarding a suitable weight matrix has resulted in a large number of specifications across hedonic spatial studies (Anselin 1988). In light of this, four different row-standardized weight matrices are considered in this study[8]:

1. $w_{ik}=1$ if distance between spatial units $\leq$3 km, 0 otherwise (defined as 3KM);
2. $w_{ik}=1$ if distance between spatial units $\leq$4 km, 0 otherwise (defined as 4KM);
3. $w_{ik}=$ inverse of Euclidean distance (defined as IWD);
4. $w_{ik}=$ inverse of Euclidean distance to the power of 1.5 (defined as $\text{IWD}_{1.5}$).

The goodness of fit measure used to determine the combination of weight matrices that best fit our dataset was the McElroy R^2 measure (McElroy 1977). Following the notation in Zhou and Kockelman (2009), this diagnostic statistics was calculated in the following way:

$$R^2=1-\frac{\xi'\Omega^{-1}\xi}{\sum_{i=1}^{M}\sum_{j=1}^{M}\hat{\sigma}^{ij}\left(\sum\sum_{t=1}^{n}(y_{it}-\bar{y}_i)(y_{it}-\bar{y}_i)\right)} \tag{7}$$

where $E[\varepsilon\varepsilon' \mid X_1, X_2, \ldots, X_M]=\Omega$, $\hat{\sigma}^{ij}$ is the ijth element in the matrix Ω^{-1}, and $\bar{y}_i$ is the mean value of the response variable (e.g., P or HHINC) for equation i.

For the housing model specification the direct, indirect, and total impacts for open space proximity are calculated following the framework in LeSage and Pace (2009). In the case of an ordinary least square estimation, indirect effects are assumed to be zero ($\rho_m=0$) and the direct effect is interpreted as the partial derivate of the response variable (either P or HHINC) with respect to the independent variable that changes. When spatially-dependent relationships are present, a change in the explanatory variable for observation i may affect the response variable of other observations. These effects are a measure of indirect impacts. Letting X_{ik} be an n by 1 column vector representing the kth explanatory variable (such a distance to wilderness areas) for observation i in the housing equation, the mathematical representation for both direct and indirect effects is defined as follows:

$$\frac{\partial \boldsymbol{P}}{\partial \boldsymbol{X}^{l}} = \begin{pmatrix} \frac{\partial P_1}{\partial x_{1k}} & \frac{\partial P_1}{\partial x_{2k}} & \cdots & \frac{\partial P_n}{\partial x_{2n}} \\ \frac{\partial P_2}{\partial x_{1k}} & \frac{\partial P_2}{\partial x_{2k}} & \cdots & \frac{\partial P_1}{\partial x_{nk}} \\ \vdots & \vdots & \ddots & \\ \frac{\partial P_n}{\partial x_{1k}} & \frac{\partial P_n}{\partial x_{2k}} & \cdots & \frac{\partial P_n}{\partial x_{nk}} \end{pmatrix} = ((I_n - \rho W)^{-1}) \begin{pmatrix} \theta_k & W_{12}\phi_k & \cdots & W_{1n}\phi_k \\ W_{21}\phi_k & \theta_k & \cdots & W_{2n}\phi_k \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\phi_k & W_{n2}\phi_k & \cdots & \theta_k \end{pmatrix}$$

In the equation above, the main diagonal elements represent direct effects (the own-partial derivatives) and the means sum row of the nondiagonal elements are indirect effects (the cross-partial derivatives) (LeSage and Pace 2009). It is also worth noticing the following three implications of equation (8). First, if both $\rho = 0$ and $\varphi_k = 0$ (e.g., Ordinary Least Squares (OLS) is the valid estimation procedure) indirect effects do not take place. Second, if $\rho \neq 0$ but $\varphi_k = 0$ (e.g., spatial lag model is the valid estimation procedure) direct effects will be nonzero and will vary with location as the values of the main diagonal elements change across observations. Third, if $\rho \neq 0$ and $\varphi_k \neq 0$ the indirect effects will be nonzero and will vary across locations as the nondiagonal elements of the matrix $(I_n - \rho W)^{-1}$ change across observations. The sum of direct and indirect effects gives the total impact of a change in explanatory variable k on observation i and can be mathematically written as: $\frac{\partial P_1}{\partial x_{1k}}$ (direct effect) + $\sum_{i=2}^{n} \frac{\partial P_1}{\partial x_{ik}}$ (indirect effects) (Kim, Phipps, and Anselin 2003; McMillen 2010; Pinkse and Slade 2010).

Data

To estimate the proposed spatial SUR model, a unique matched sample of household-income housing units is used at the household level. In this sample, each observation includes reported household income (2007$), household characteristics (e.g., race, employment status), home value, and housing characteristics. The data for the housing and income equations come from two different sources: 1) a 2007 survey for the Southwest Region in the U.S. titled "Attitudes, Beliefs, and Values towards National Forests and National Forest Management", referred hereafter as the 2007 Region 3 Survey (McCollum et al. 2008); and 2) housing characteristics purchased from a commercial marketing vendor, PrimeraSource.[9] It is important to note that household characteristics refer to the person who completed the survey at the time it was conducted. The housing data was purchased in 2008 after the final round of the 2007 Region 3 Survey was completed, as the objective was to obtain housing data for those who responded to this survey.

The sample for the income equation is restricted to households 18 years and older. Characteristics for these households (e.g., income, education, race, employment status) were obtained from standard demographic questions included in the 2007 Region 3 Survey.

For the purpose of this analysis, this data was subsequently matched with housing data obtained from PrimeraSource, a commercial vendor. As only minimal responses were received from the states of TX and OK and the housing information for NM had significant gaps (NM is a real estate sales price nondisclosure state, see Berrens and McKee 2004), this analysis focuses on the state of AZ.[10] While 2,998 usable survey responses were received from AZ, the following issues did not allow the inclusion of all of the 2,998 observations in this study: missing household demographic information, missing housing information, and no neighboring houses for the weight matrix defined as 3KM (e.g., closest home from house i is located further than the 3 km threshold).[11] As a result, the estimates reported in this study are based on 1,014 observations.

Table 1. Definitions and Descriptive Statistics of Geographic Variables

Variable	Definition (source)	Mean	Std. Dev.
LNWILD	Distance to nearest Congresionally-designated wilderness area, miles (GIS, USFS)	30.03	7.42
LNFOREST	Distance to nearest National forest area. miles (GIS, USFS)	25.38	17.50
LNHOSP	Distance to nearest hospital, miles (GIS, U.S. Bureau of the Census)	3.58	2.99
LNURBAN	Distance to nearest urbanized area. miles (GIS, U.S. Bureau of the Census)	6.67	3.02
LNSTPARK	Distance to nearest State park, miles (GIS. U.S. Bureau of the Census)	30.76	13.24
LNCYPARK	Distance to nearest city park, miles (GIS. U.S. Bureau of the Census)	0.84	1.84
LNPMONU	Distance to nearest Congresionally-protected National Monument, miles (GIS. U.S. Bureau of the Census)	53.6	39.6
LNUMONU	Distance to nearest Unprotected Monument, miles (GIS, U.S. Bureau of the Census)	46.9	25.5
LNHIGHWAY	Distance to nearest highway, miles (GIS. U.S. Department of Commerce)	6.62	5.12
LNGOLF	Distance to nearest golf course, miles (GIS. U.S. Bureau of the Census)	5.11	3.17
LNLANDFILL	Distance to nearest active landfill, miles (GIS, ADEQ)	9.78	5.34
LNWATER	Distance to nearest Outstanding Arizona Water, miles (GIS, ADEQ)	93.28	17.83

Sources: USFS: United States Forest Service Southwestern Region, http://www.fs.fed.us/r3/gis/datasets.shtnd and http://roadless.fs.fed.us. ADEQ: Arizona Department of Environmental Quality, U.S. Bureau of the Census, and U.S. Department of Commerce, http://agic.az.gov/portal/dataList.do?sort=theme&dataset=54.

The dependent variables are LNHHINC, the natural log of annual household income as indicated by respondents in the 2007 Region 3 survey, and LNHVALUE, the natural log of home values. As reported in Table 2, the mean household income is $65,423 and the mean home value is $165,128 in 2007$.[12] It is important to note that home prices are estimated market values as opposed to values obtained from actual market transactions (e.g., from selling a house). The main reason is that housing data was purchased based on whether the particular household responded to the 2007 Region 3 Survey and not on whether the house was sold in 2007.

The primary independent variables of interest in the empirical estimates are measures of natural characteristics, and specifically those measures that relate to forest resources. The site-specific characteristics that have been gathered for this analysis include road mile distance to different measures of forest area, water features, landfill sites, and urban characteristics.

TABLE 2. DEFINITIONS AND DESCRIPTIVE STATISTICS OF HOUSING AND INCOME VARIABLES (N=1,014)

Variable	Definition	Mean	Std. Dev.
Housing variables			
LNHVALUE	House sale value (2007$)	165,128	85,706
BEDROOMS	Total number of bedrooms	2.61	1.19
BATHROOMS	Total number of bathrooms	1.54	1.07
HAGE	Age of a house (2007 - year built)	31.53	16.06
LOTSIZE	Size of a house (acres)	0.20	0.30
Income variables			
LNINC	Annual Household income (2007$)	65,423	25,319
EDUC	Years of education	7.04	2.45
EXP	Years of working experience	25.34	18.75
EXP2	Years of working experience squared	750.12	920.13
WORKPT	1 = work part-time, 0 else	0.09	0.34
RETIRED	1 = retired, 0 else	0.18	0.21
HOMEMAKER	1 = homemaker. 0 else	0.25	0.43
OTHSTATUS	1 = full-time student, part-time student, active duty military, unemployed, 0 other	0.09	0.54
HISPANIC	1 = Hispanic descent, 0 else	0.27	0.36
MALE	Gender: Male, binary	0.72	0.54
LIVINGNRE	Make a living from a job that depends directly on natural resources (e.g., ranching, mining, guiding hunters or recreation users, working in a saw mill), binary	0.05	0.16

The variables that measure forest characteristics are logged road mile distance from house *i* to its closest National Forest land (LNFOREST, which includes Wilderness Areas and National Parks), and Congressionally-designated Wilderness Area (LNWILD).[13] To be clear, LNWILD is a subset of LNFOREST. These areas are expected to be an amenity (e.g., $\theta_f < 0$ in the housing equation and $\delta_f > 0$ in the income equation) but the designation of LNFOREST areas for multiple uses (including recreation and extractive uses) distinguishes these lands from wilderness lands. These areas are expected to carry a positive implicit price reflective of recreation, ecosystem services, and passive use values (Phillips 2004). Similarly, the other site-specific characteristics used in estimation include closest logged distance to outstanding waters (LNWATER), to State parks (LNSTPARKS), to city parks (LNCYPARKS) to Congressionally-protected National Monuments (LNPNM), to "unprotected" Monuments (LNMONU), and logged distance to a landfill (LNLANDFILL).[14] It is of importance to note that LNWATER LNSTPARKS overlap geographically with National Forest lands. In particular, 63 percent or 170 miles of Outstanding Waters occur on National Forest areas and 48 percent or 14 State parks are located within a National Forest.

The independent variables for the housing-price equation include the number of bedrooms (BROOMS), bathrooms (BATHROOMS), structure age (AGE), and property acreage (LOTSIZE). In terms of urban characteristics, the variables included are logged road mile distance to highway (LNHIGHWAY), distance to a hospital (LNHOSPITAL), distance to nearest urbanized area

(LNURBAN), and distance to a golf course (LNGOLF), which includes municipal course, semiprivate courses (e.g., nonmember can play), and private courses (e.g., membership required to play). The income equation independent variables include categorical variables for employment status, race indicators, gender (MALE) and whether the household's primary wage earners' job depends directly on natural resources (LIVINGNRE). Tables 1 and 2 provide variable definitions and descriptive statistics.

Results

To determine the model specification that best fits the data, this study follows the steps describe in Table 3 (Elhorst 2010). Prior beliefs about the nature of spatial dependence are tested using a series of diagnostics tests reported in Table 4.[15] The LM test derived by Anselin (1988) allows for testing residual spatial error autocorrelation in the presence of a spatially lagged dependent variable ($LM_{\lambda/\rho}$) and for testing spatial lag autocorrelation in the presence of spatial error dependency ($LM_{\rho/\lambda}$). In the first case, a spatial lag model for the housing equation is estimated via a maximum likelihood approach (ML) and the LM test is calculated with the null hypothesis being $\lambda_{\text{house}} = 0$ as outlined in and Bera (1998). In a similar manner, the LM test for spatial lag autocorrelation in the presence of spatial error autocorrelation is derived by first estimating a spatial error model (Anselin et al. 1996; Zhou and Kockelman 2009). In this case, the null hypothesis is $\rho = 0$. The LM tests have a chi-squared (χ^2) distribution with one degree of freedom (e.g., the restriction that $\lambda = 0$ or $\rho = 0$). The factor constraint tests suggest that if the null hypothesis cannot be rejected, the spatial Durbin model simplifies either to a spatial lag model (e.g., spatially lagged independent variables are jointly significant: $\Upsilon \neq 0$, $\eta \neq 0$, and $\varphi \neq 0$) or to a spatial error model (e.g., $\Upsilon = -\rho\beta$, $\eta = -\rho\phi$, and $\varphi = -\rho\theta$).

Table 4 reports the χ^2 values for the different tests. In all the cases, the null hypotheses are rejected. These findings suggest that a spatial Durbin model specification is the most appropriate for the housing equation. In the case of the income equation, the model specification used in the paper is a spatial error model due to the explanatory variables included in this equation (e.g., dummy variables) and the little or no theoretic support for representing spatial dependence via a spatial lag or a spatial Durbin process.

The spatial SUR coefficients are reported in Table 5. This model was estimated using the maximum likelihood approach outlined in Anselin (1988).[16] The pair of weight matrices that yielded the highest McElroy R^2 value was 4KM (spatial lag) and IWD (spatial error).[17] This preferred model shows a correlation of 0.14 that is statistically significant at a 99 percent confidence level, supporting the use of the SUR approach. The second best model (4KM for the spatial lag and 3KM for the spatial error) indicate that the results do not necessarily depend on the weight matrices being specified. It is worth mentioning that a spatial Breusch-Pagan test revealed the presence of some residual heteroskedasticity in the spatial Durbin specification (housing equation). A plausible robust estimator is the heteroskedasticity and autocorrelation consistent covariance matrix estimator proposed by Kelejian and Prucha (2007). As in this study the spatial models are estimated using a maximum likelihood estimation technique, a multiplicative covariance correction is used to control for heteroskedasticity (Harvey 1976).[18] In this case, the general heteroskedasticity specification form is (Greene 2003: 232):

$$\sigma_i^2 = \sigma^2 \exp(z'a) \tag{9}$$

where z is a vector of observable variables that are believed to determine the variance and α is a vector of the coefficients. As in the case of this study, a log-log form is used to model the housing equation, the specification above becomes:

Table 3. Model Identification Process

Steps	Test	H_0	H_1	Model Implications
1	LM-error	Assuming no spatial lag autocorrelation ($\rho = 0$). there is no residual autocorrelation ($\lambda = 0$).	Spatial residual autocorrelation ($\lambda \neq 0$).	Rejection of H_0 implies estimating a spatial error model
2	LM-lag	Assuming no spatial residual autocorrelation ($\lambda = 0$). there is no spatial lag autocorrelation ($\rho = 0$).	Spatial lag autocorrelation ($\rho \neq 0$),	Rejection of H_0 implies estimating a spatial error model
	RLM-error	No spatial residual autocorrelation ($\lambda = 0$). after correcting for local spatial lag dependence	Spatial residual autocorrelation ($\lambda \neq 0$).	Rejection of H_0 implies estimating a spatial error model
	RLM-lag	No spatial lag autocorrelation ($\lambda = 0$). after correcting for local spatial error dependence	Spatial lag autocorrelation ($\rho \neq$).	Rejection of H_0 implies estimating a spatial error model
3	Factor constraint hypothesis	$\gamma+\rho\beta=0$, $\eta+\rho\varphi=0$, $\phi+\rho\theta=0$	$\gamma+\rho\beta \neq 0$, $\eta+\rho\varphi \neq 0$, $\phi+\rho\theta \neq 0$	Rejection of H_0 implies estimating a spatial Durbin model (unrestricted model). If H_0 is not rejected, estimate spatial error model.

Table 4. Spatial Test Results

	Housing equation	Income equation
Spatial Lag, OLS model		
LM_{ρ}	447.05	27.57
LM_{ρ}^{robust}	28.86	31.90
Spatial Error. OLS model		
LM_{λ}	535.72	10.31
LM_{λ}^{robust}	117.53	14.64
Factor constraint, spatial Durbin model		
$LM_{\gamma,\eta,\phi=0}$	83.13 (0.00)*	
$LM_{\gamma+\rho\beta=0,\eta+\rho\varphi=0,\phi+\rho\theta=0}$	82.14 (0.00)*	

*Number in parenthesis denotes *P* value.

$$\sigma_i^2 = \sigma^2 \prod_{m=1}^{M} z_{im}^{a_m} \tag{10}$$

where z is replaced by the logs of the explanatory variables.

Estimates for structural characteristics and the household's human characteristics for the housing and income equations are all statistically significant and have expected signs. For instance, home values increase with lot size, number of rooms, and year built (i.e., the more recent the house was built the higher its value). Income vary significantly depending on years of education, gender (household males tend to earn higher income compared to females), and race (Whites non-Hispanic, the base case, earn significantly higher income than Hispanic household).

The spatial lag autocorrelation coefficient (ρ) ranges between 0.26 and 0.38 and is statistically significant regardless of the weight matrix (W) specified (3KM, 4KM, IWD, or $IWD_{1.5}$), indicating that home values are positively related in space. This result underscores the importance of accounting for spatial dependence.

The estimated coefficients for WILD and FOREST support the hypothesis that these different types of forest areas are positive amenities for individuals. The negative signs in the housing equation suggest that the closer a home is located to one of these areas the higher its value. In the labor market, individuals are trading income for proximity to forests as indicated by the positive coefficients for these variables (i.e., households closer to a forest area have lower household income). A similar relationship is found for the other natural amenities included in the model. For instance, households are willing to earn a lower income level for living closer to lake areas or outstanding waters and home values increase the closer a house is located from these amenities.

The positive implicit values of proximity to National Forest and Wilderness Areas give rise to a relevant policy question: Does the value of Wilderness Areas (the subset land) represent an extra "bump" in the value of National Forest areas (the inclusive good)? While the inclusion of National Forest and Wilderness Areas in the same model mitigates a potential upward bias in the coefficient for LNFOREST (e.g., omitted variable bias), wilderness designation may not necessarily represent an additional implicit value to that of National Forest areas. For instance, the road mile distance from house *i* to its closest National Forest may coincide with its closest wilderness area. In this study, for 50 observations or 5 percent of the sample the closest National Forest area is also the closest

TABLE 5. ESTIMATION RESULTS

	Housing		
	Coeff	Lagged coeff	Income Coeff
BROOMS	0.062***	−0.048***	
BATHROOMS	0.053***	0.049***	
BHAGE	−0.028***	−0.017***	
LOTSIZE	0.125***	−0.103***	
LNHIGHWAY	−0.01**	−0.070	
LNHOSPITAL	0.002	0.001	
LNGOLF	0.013	−0.011	
EXP			0.034**
EXP^2			0.0092
EDUC			0.088***
WORKPT			−0.115*
RETIRED			−0.286**
HOMEMAKER			0.047*
OTHSTATUS			−0.038
HISPANIC			−0.172*
MALE			0.224***
LIVINGXRE			−0.041
LNWILD	−0.021*	0.018*	0.014*
LNFOREST	−0.032*	0.038	0.018*
LNUMONU	−0.023	0.008	0.004
LNPMONU	−0.014	0.006	0.057
LNSPFUND	0.009	−0.009	0.044
LNURBAN	0.014**	−0.049*	0.067**
LNWATER	−0.044	0.047	0.132
LNSTPARK	−0.015*	0.028	0.037*
LNCYPARK	−0.025*	0.001	0.018*
ρ	0.356***		
λ			0.166***
McElroy R^2		0.55	
N		1,014	
Resitdn. COIT.		0.14	

*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Wilderness Area.[19] In these cases, the implicit value of wilderness designation may not represent a "bump" in the value of National Forest, and therefore, would result in double-counting if added to the implicit value of National Forest areas.

In the case of other geographic features, results indicate that housing prices and income increase the closer a household lives from an urbanized area (defined as a territory with 50,000 or more individuals). This suggests that while people value proximity to natural amenities they also benefit by

Table 6. Marginal Effects for Direct, Indirect, and Total Impacts of Proximity to Natural Amenities and Structural Housing Characteristics

	Direct	Housing marketindirect	Total	Labor marketdirect/total
BROOMS	0.0581***	−0.0112***	0.0469***	
	($9,594)	(−$1,849)	($7,746)	
BATHROOMS	0.0417***	0.0086	0.0503*	
	($6,886)	($1,420)	($8,306)	
BHAGE	−0.014**	−0.0049	−0.0189*	
	(−$2,312)	(−$809)	(−$3,121)	
LOTSIZE	0419***	−0.0142***	0.1048***	
	($19,650)	(−$2,345)	($17,305)	
EDUC				0.088***
				($5,757)
LNWILD	−0.0136*	0.0097*	−0.0039*	0.014*
	(−$2,246)	($1,602)	(−$644)	($916)
LNFOREST	−0.0292*	0.0230*	−0.0062*	0.018*
	(−$4,822)	($3,798)	(−$1,204)	($1,178)
LNWATER	−0.0257	0.0043	−0.0214	0.132
	(−$4,244)	($710)	(−$3,534)	($8,636)
LNSTPARK	−0.008*	0.011	0.003	0.037*
	(−$1,321)	($1,817)	($496)	($2,421)
LNCYPARK	−0.012	0.007*	−0.005*	0.018*
	(−$1,982)	($1,156)	(−$826)	($1,178)

*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. ( ) denotes marginal implicit prices evaluated at the sample house mean of $165,128 and the sample household income mean of $65,423.

living close to urban areas. In terms of a disamenity, landfill sites (LNLANDFILL) does not have a statistically significant effect.

The presence of spatial processes requires the calculation of total implicit prices to properly understand the magnitude of the effect of each geographic feature on home values and household income. Estimated direct, indirect, and total impacts for selected variables are presented in Table 6. In the case of basic house characteristics number of bedrooms, number of bathrooms, and house age have the expected direct impact on house values: an additional bedroom or bathroom increases the price by 5.8 percent and 4.17, respectively, while age decreases a home value by 1.4 percent. In the case of distance to natural amenities, the primary variables of interest in this study, the direct effects are significant (10 percent level), except for distance to nearest outstanding water (LNWATER) and distance to city parks (LNCYPARK). A decrease in proximity to wilderness areas by 1 mile (while holding all the other attributes constant), increases home values by 2.1 percent or $2,246 and decreases household income by 1.4 percent or $916. Similarly, proximity to forest areas (inclusive good) has a positive direct effect on home values ($4,822) and a negative direct effect on household

income ($1,178). The other attributes in this category have similar impacts on the respective response variables.

For the housing market, the estimation results also show that housing characteristics as well as distance to natural amenities have indirect effects on neighboring houses (e.g., the impact that a change in explanatory variable *k* has on the price of neighbouring houses). These effects differ in significance, sign, and size of the coefficients compared to the direct effects. The estimated coefficient for the number of rooms and lot size are significant at the 1 percentage significance level. The addition of one more room in house *i* increases the value of the house (direct effect) but may have a negative impact on the value of surrounding houses (indirect effect). Having a higher number of rooms or a bigger lot size compared to neighboring houses could result in house *i* being offered at a higher price than the surrounding houses. With respect to natural amenities, three variables are significant at the 10 percentage significance level: distance to wilderness areas (LNWILD), distance to forest areas (LNFOREST), and distance to city Parks (LNCYPARK). In the case of LNWILD and LNFOREST, proximity to wilderness and forest areas for house *i* has a negative impact on neighboring home values, 0.0097 ($1,602) and 0.0230 ($3,798), respectively. These results suggest that these types of open spaces are amenities to houses surrounding house *i*.

When specifying a Spatial Durbin model, there are three important observations that can be drawn from the estimated coefficients. First, the magnitude of the nonlagged explanatory variables' coefficients reported in Table 5 for the housing equation is different compared to the direct effects (Table 6). As discussed in LeSage and Pace (2009) and Seldadyo, Elhorst, and De Haan (2010), this difference is due to the feedback effect. In the case of the natural amenities, these feedback effects are quite small (0.0070 for LNSTPARK, 0.0028 for LNFOREST, and 0.0074 for LNWILD). The magnitude of these effects is in line with those found in LeSage and Pace (2009). Second, interpreting the coefficients for spatial lagged explanatory variables as the indirect effects could lead to wrong conclusions. For instance, in the case of forest areas (LNFOREST) and city parks (LNCYPARK) the spatially lagged variables (0.038 and 0.001) are not statistically significant. However, the estimated indirect effects for these variables are significant at the 10 percent confidence level. Third, the sum of the nonspatially lagged coefficient and the spatially lagged coefficient for a given variable does not necessarily have to be similar to total effects (direct effect + indirect effect). For instance, for water amenity (LNWATER) the estimated total effects are −0.0214 compared to 0.003 (calculate by summing up the nonspatially lagged coefficient and the spatially lagged coefficient).

Conclusions

Using a unique micro-level data set, this study has examined proximity (road distance) to a set of natural amenities as determinants of spatial variations in housing prices and income for the State of Arizona. The set of natural amenities includes National Forest lands, U.S. Congressionally-designated federal Wilderness Areas, National Monuments and state-designated protected waters (OAW). The analysis also controls for proximity effects from local (municipal, county or state) parks and golf courses. In particular, the presence of off-site benefits, one component of the TEV of protected lands and waters, suggests that individual preferences for housing and job location are partially based on proximity to these areas and other environmental amenities. These findings are in line with previous studies that have shown that the value of land and water amenities is not simply as intermediate inputs in the production of market goods, such as wood products. In a prior regional study in which the percentage of National Forest areas within a predefined administrative boundary is used to estimate implicit values, Hand et al. (2008b) show that Wilderness area and National Forest areas

carry implicit prices in the housing and labor markets that range between $27 and $85 per square mile annually in the Southwest U.S. (Arizona and New Mexico). It is important to note that off-site benefits, such as proximity to a natural amenity, are components of the larger bundle of ecosystem services and nonmarket benefits that such amenities may offer (Loomis and Richardson 2000; Champ et al. 2003).

After controlling for housing, neighborhood, and the household's human capital characteristics and location-specific amenities, results show that the average annual total implicit price per household for living and working proximal to National Forest areas (which includes Wilderness Areas) is $2,382 compared to $1,560 for Wilderness Areas. These values are based on a GIS road network analysis that calculates the road mile distance from a house to one of these natural amenities. The presence of compensating housing-price and income differentials suggest that individuals' are choosing where to live and work partially based on proximity to natural amenities.

The importance of spatial relationships is confirmed; all spatial lag autocorrelation coefficients are statistically significant and positive, indicating that omitting the housing prices of neighboring homes would result in biased results. Spatial error autocorrelation also appears to be present, although the significance of the spatial error coefficients (e.g., λ_{house} and λ_{hhinc}) is not identifiable in the SUR estimation process.

As argued elsewhere with aggregate Census data for the region (Hand et al. 2008b), and supported here with the micro-level data for AZ, an implication of these results is that travel cost-based valuation techniques would not reflect the full price of recreation site access, and may lead to underestimates of such values (Randall 1994; Schmidt and Courant 2006). If preferences for natural amenities are related to recreation travel, then observed travel costs would be endogenous. In the present context, results show that individuals in AZ are paying for shorter road distances to natural amenities, many of which may be valued for their recreational opportunities. Recreation-minded individuals choosing to pay for better recreation access would then pay lower travel costs when using nearby recreation sites. A study of these recreationists using a travel cost method would underestimate the value of recreation site access by ignoring the price paid for access through labor and housing markets.

Further, the potential for a zone effect or ecological fallacy is mitigated here with the use of micro-level data. In many cases, the results found based on aggregated administrative boundaries (such as Census tracts or Census blocks) are implicitly assumed to apply to a smaller scale, such as individual observations. In this study, as the level of observation are households identified to geocoded points, distances to a natural amenity are not based on a representative agent home or an arbitrarily defined centroid. A possible extension of this study is to test the effect of ecological fallacy by estimating a hedonic model where locations are aggregated to match census tract areas and compare the results with those found here.

The spatially explicit compensating differentials can inform decisions about the protection or development of public land, such as Wilderness or National Monument designations, or a mine siting decision. For example, the Forest Jobs and Recreation Act (proposed in the U.S. Senate in 2011) would have designated as Wilderness an additional 677,000 acres of Federal land, and removed 76,000 acres of land from consideration for Wilderness designation in the U.S. State of Montana.[20] More recently (and closer to the study area), President Obama in March 2013 designated approximately 242,000 acres of Federal land in northern New Mexico for protection as a National Monument.[21] The estimated total implicit prices of proximity to National Monuments suggest that similar designations in Arizona would yield positive benefits for individuals living near any such new designations. Further, the spatially explicit model can provide insight on the spatial distribution benefits for policies that change management and designation status of federally protected lands.

The finding of spatial dependence also raises questions about decisions and interactions among jurisdictions with nearby federally protected lands. The empirical findings are useful for inferring, in dollar terms, the preferences residents have for location-specific amenities, but cannot adequately describe how the existence and preferences for federally protected areas may affect local investments in amenities or environmental improvements. A fruitful area of future research could extend models of jurisdictional interactions (e.g., Brueckner 2003) to account for federally provided amenities that affect housing and labor markets.

Finally, future studies can relax the assumption that the estimated coefficients are constant in space by introducing spatial heterogeneity. It is important to note that the estimation of the hedonic models assumes spatial equilibrium for the housing and labor markets. As the presence of natural amenities may in part explain net migration patterns, such an assumption could be too restrictive.

NOTES

1. In this study, forest areas refer to National Forest lands owned by the federal government and managed by the United States Forest Service (USFS). Wilderness Areas include USFS-managed and non-USFS managed Wilderness Areas. In particular, proximity to forest lands is calculated for six National Forests: Apache-Sitgreaves, Coconino, Coronado, Kaibab, Prescott, and Tonto. Wilderness Areas are Congressionally-protected land under the 1964 Wilderness Act. Outstanding Arizona Waters (OAW) refers to surface water that is managed as protected water under rule R18-11-115 (Arizona Department of Environmental Quality A.A.C. R18-11-112). The Clean Water Act requires that the surface waters of each state be classified according to designated uses (US Environmental Protection Agency, 1989). The "Outstanding Water" designation falls under the Antidegradation Policy of the Clean Water Act. While the Arizona Department of Environmental Quality can classify waterbody as Outstanding Water by rule, private citizens can nominate a surface water for classification. Thus, OAW includes roughly 270 miles of protected river reaches across 22 sites, with a mix of public and private land ownership.
2. Zone and scale effects are referred to as the Modifiable Areal Unit problem (Openshaw 1984).
3. National Forest lands include Wilderness Areas and are owned by the federal government and managed by the United States Forest Service. Wilderness Areas are Congressionally-protected land under the 1964 Wilderness Act, and Outstanding Arizona Waters refers to surface water that is managed as protected water under state rule R18-11-115.
4. A second spatial effect, which is not addressed in this model, is spatial heterogeneity. This refers to spatial relationships where functional form requires parameters vary with locations.
5. We thank to an anonymous reviewer for suggesting this connection.
6. In this case, there are two equations: the housing price and the household income equations.
7. Both the spatial lag and the spatial error models are special cases of the spatial Durbin model. A spatial lag model can be derived from equation (6) by setting the coefficients of the lagged independent variables (Υ, η, φ) equal to zero. If instead, the following restrictions are empirically valid, then the spatial Durbin model becomes a spatial error model (equation 5): $\Upsilon\ \rho\beta$, $\eta\ \rho\varphi$, and $\phi\ \rho\theta$.
8. These weight matrices were created using RGui software.
9. The 2007 Region 3 Survey was conducted by the Department of Economics, University of New Mexico in cooperation with the US Department of Agriculture's Forest Service, Rocky Mountain Research Station. This project involved a large general population sample, multi-mode survey (mail survey mode with a web-based survey mode option), with multiple language options (versions in both English and Spanish). The target population included all households in the Southwest Region (AZ, NM, and small parts of TX and OK). The survey instrument constructed based on five focus groups. The overall response rate was 21.53 percent. For further details see McCollum et al. (2008).
10. The breakdown of total responses received by state is: 3,509 for NM, 2,998 for AZ, 56 for OK, and 272 for TX.
11. In AZ, the number of nonresponses for the demographic section by characteristics are: 55 for gender, 30 for ethnicity and 35 for years of education. Lack of housing information includes: 268 observations without any type of information, 289 without home values, 14 without year built, 612 without lot size, and 613 without number of rooms. Sixty-eight observations had to be dropped for missing neighboring houses, by the 3KM weight matrix criterion.

12. The mean value for home values is $171,403. Since home values were assessed in 2008, the price in 2007 dollars is $165,128 given a Consumer Price Index conversion factor of 1.038.
13. To calculate the road mile distance to the closest natural amenity the OD cost matrix function in ArcMap GIS was used. This function calculates the distance in miles from an origin (e.g., house) to a destination (Wilderness Area) along a predefined road network.
14. In the State of Arizona, there are 35 Monuments. 18 out the 35 are protected areas or National Monuments under the Antiquities Act of 1906. The rest are monuments that could potentially become National Monuments. National Monuments are managed by the U.S. Forest Service and the Bureau of Land Management.
15. An alternative to the LM test is the well-known Moran's I, which indicates which indicates whether or not there is spatial autocorrelation after estimating an OLS regression but does not identify the cause of spatial dependence (Cliff and Ord 1972).
16. An alternative estimation approach is the instrumental variable and generalized method of moments outlined in Kelejian and Prucha (2010). However, as in this study a spatial Durbin model for the housing market is specified, spatially lagged exogenous variables cannot be used as instruments for identifying WP in the first stage. This limitation may significantly affect the validity of other instruments used (e.g., $W^2\mathbf{Q}$ or $W^3\mathbf{Q}$) resulting in weak instrument problems. For a thorough discussion on this topic, see Pace, LeSage, and Zhu (2012).
17. For this specification, the McElroy R^2 was 0.55 versus to 0.37 to 0.51 for the other 11 cases.
18. The spatial Breusch-Pagan heteroskedasticity tests for the housing and income equations are 36.6014 (significant at a 5 percent level) and 26.0862 (not statistically significant), respectively.
19. The 5 percent was calculated assuming a 1-mile threshold difference. The latter is the absolute value of the difference between the distance from a given property to its closest National Forest and to its closest Wilderness Area.
20. Senate Bill 268, Forest Jobs and Recreation Act of 2011, 112th Congress. The bill was not passed out of committee in the Senate. Bill text available at: http://thomas.loc.gov/cgi-bin/query/z?c112:S.268:, accessed March 26, 2013.
21. The Rio Grande Del Norte National Monument was established by Presidential Proclamation on March 25, 2013. See: http://www.whitehouse.gov/the-press-office/2013/03/25/presidential-proclamation-r-o-grande-del-norte-national-monument, accessed March 26, 2013.

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