The Role of Forests as Natural Amenities: A Seemingly Unrelated Regression Model with Two Spatial Processes

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Abstract:

Natural amenities may offer opportunities that people value and make economic decisions over when choosing a residential location. The objective of this paper is to test this hypothesis by examining spatial variations in wage and housing prices in the presence of forest amenities in a study of Arizona. Spatial hedonic regressions of housing prices and wages indicate that the average total implicit price for forest areas is $1,090 per mile compared to $696 for wilderness areas, annually. These 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. The presence of compensating differentials implies that monetary evaluation techniques, such as the travel cost method, would not reflect the full price of recreation site access, and may lead to underestimates of such values.

Introduction

The tradeoff between land costs and commuting costs has been traditionally cited as one of the main factors to explain a household's choice of residential location (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 (Sander and Testa, 2009; Glaeser et al., 2008). However, as empirical evidence has raised questions about the validity of this theory (see Wu, 2010; Glaeser et al., 2008), 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 determinants of residential location (Loomis and Richardson, 2000; Schmidt and Courant, 2006; Hand et al., 2008; Izon et al., 2010). 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 et al. 1999).

Natural amenities may offer opportunities that people value and make economic decisions over when choosing a residential location. These amenities generate easily measurable economic benefits, such as tourism and non-economic benefits (habitat and soil quality protection), and other passive use values that are not necessarily captured in market prices. 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. 2008). In this case, a lower labor income (first check) may be compensated by a larger second paycheck (e.g., access to natural amenities).

The objective of this paper is to test this hypothesis by examining spatial variations in wage and housing prices in the presence of forest amenities in a study of Arizona. Since natural amenities generate multiple beneficial end uses, there have been competing allocation schemes for these resources.[1] 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, looking at wage and housing prices differentials (off-site benefits). Thus, this paper reports estimates for a portion of the total economic value (TEV) of these amenities. For instance, they may also be on-site recreation values and passive values that are not captured in wage or housing prices.[2]

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[1] This has clearly been the case in the policy debate about Wilderness Areas and Inventories Roadless Areas that centers on the question of how these public lands should be managed and allocated. Wilderness areas are congressionally protected from any type 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 this region has been anything but negative and empirical evidence suggests that spending for outdoor recreational activities have not been significantly impacted by the recent great depression (Loomis and Keske 2012). The policy debate about IRAs centers on whether to manage these lands as wilderness areas (Aarons 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.

[2] Loomis (1996) reviews evidence from various contingent valuation studies that passive use values may represent a significant percentage, and sometimes a majority proportion, of the total economic value (TEV) associated with protected forest areas in the U.S. This suggests that off-

The empirical framework and the nature of the data use in this study offer the following contributions to the current literature. Firstly, this paper addresses the possibility of spatially-dependent relationships by estimating spatial regression models. The underlying spatial relationships among observations were determined by applying Lagrange Multiplier (LM) tests for the co-existence of spatial lag and spatial error processes. Secondly, we estimate the effect on housing and labor markets of site-specific characteristics, such as forest areas, wilderness, superfund sites, and outstanding waters, based on a Geographic Information System (GIS) road network analysis.[3] These variables represent the road mile distance from house *i* to its closest natural amenity within each category.[4] 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. Thirdly, to the degree that preferences for forests are related to recreation travel, observed travel cost would be endogenous. People choosing to live close to

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site amenity values to residents, as measured here, might represent just one of several significant components of the TEV.

[3] Forest areas refer to lands under federal supervision for the purposes of conserving water, timber, wildlife, fish, and other renewable resources and providing public recreation areas. Wilderness areas are congressionally protected land under the 1964 Wilderness Act. Outstanding Arizona Waters 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).

[4] 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.

natural amenities would reveal an implicit value for such benefits that is lower than their willingness to pay. This would suggest that the travel cost method (TCM) would not reflect the full price of recreation site access, and may lead to underestimates of such values (Hand et al., 2008; Schmidt and Courant, 2006).

Lastly, as it is common in many studies that look at the role of forest amenities (e.g., Schmidt and Courant 2006; Hand et al. 2008; Izon et al. 2010), the aggregated nature of the data raises some methodological issues. Since the geographic data used in these studies pertain to aggregated administrative census boundaries (such as Census tracts and Public Use Microdata Areas, PUMAs), a pressing issue is the possibility of measurement errors due to geographic aggregation bias. This bias refers to differences in empirical results depending on the spatial arrangement of zones or the scale used to estimate the econometric models (Doll et al. 2004).[5] 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). To mitigate this issue, this study uses micro-level data by matching a sample of wage-earner housing units at the household level. For instance, proximity to a natural amenity is measured based on individual house locations as opposed to an arbitrary defined administrative boundary centroid.

[5] The zone and scale effects are also referred to as the Modifiable Areal Unit problem (MAUP) (Openshaw 1984).

3.1 Hedonic Empirical Framework

In order to address the empirical question of whether forest characteristics, such as wilderness lands and inventoried roadless areas are in fact amenities that significantly affect housing-price and wage differentials in Arizona, this paper uses hedonic theory. In this section, hedonic frameworks to analyze households' location decisions in the presence of natural amenities and a theoretical discussion on spatial-dependence relationships are presented to inform the empirical approach. In hedonic price studies, the hypothesis is that visual or proximal access to some set of environmental amenity and disamenity characteristics gets capitalized into the housing and labor markets. The hedonic pricing method decomposes the statistical variation in prices for a heterogeneous good (e.g., home values or wages) to isolate the contribution of individual attributes or characteristics of the good (Taylor 2003).

The underlying model used in this paper for the empirical analysis follows that in Roback (1982). In the context of regional forest, it is assumed that households derive utility over a bundle of characteristics composed of goods consumed (C, a numeraire good), land space (L, sold at price *p*), and location-specific environmental amenities Q. Such a bundle varies across the region depending on where the household lives and works, which gives rise to the hypothesis of compensating differentials in housing and labor markets. Households supply labor to firms in exchange for a wage *w*. In particular, a household in location *j* maximizes utility by choosing C_j and L_j, conditional on natural amenities q_j and subject to the budge constraint, such that:

$$\bar{V} = V(p_j, w_j; Q_j) \text{ for } j = 1,\ldots,J \qquad (1)$$

where V is the indirect utility function for household in location *j* and $\bar{V}$ is the utility level for the whole region (in this case Arizona) when the labor and housing markets are in equilibrium. Since forest amenities are assumed to be fixed for a particular location, land prices and wages must adjust to equalize utility at $\bar{V}$ in all locations. Since iso-utility curves are upward sloping in the (w, p)-plane, this suggests that for a given level of amenities, a location with higher house prices must also have higher wages to achieve regional equilibrium (Wu and Gopinath 2008).

Firms, the suppliers and producers of good C, are assumed to operate in a perfectly competitive market with a unit cost function that depends on the price of land, wages, and forest characteristics, such that in equilibrium:

$$C(p_j, w_j; Q_j) = 1 \text{ for } j = 1,\ldots,J \tag{2}$$

The household equilibrium condition (equation 1) and the firms' production cost equality condition (equation 2) determine the general equilibrium level of wage and housing prices. Since at equilibrium $\partial C = \partial V = 0$, differentiating equations (1) and (2) with respect to Q and solving for $\partial w / \partial Q$ and $\partial p / \partial Q$ yields the following implicit price expressions:

$$\frac{\partial p}{\partial Q} = \frac{W_W C_Q - V_Q C_W}{\Delta} \tag{3}$$

$$\frac{\partial w}{\partial Q} = \frac{V_Q C_P - V_P C_Q}{\Delta} \tag{4}$$

where $\Delta = -V_W C_P + V_P C_W < 0$

Equations (3) and (4) represent the effect of forest amenities on wages (labor market) and housing prices, respectively, and their sign depends on how this natural amenity affects firms' productivity, C_Q (Roback 1982). Let's say that two locations share the same characteristics but one is located closer to forest areas. For a given wage rate and assuming that forest amenities do not affect firms' productivity (e.g., $C_Q = 0$), the utility level is higher for individuals living in the location closer to amenable forest areas (e.g., $V_Q > 0$), and therefore, housing prices in this location should be higher for equation (1) to hold (e.g., same utility level ($\bar{V}$)across all locations).[6] In equilibrium, individuals trade proximity to forest areas for lower wages and firms substitute labor for capital, due to lower wages and higher cost of capital (Wu and Gopinath 2008). If firms' costs decrease with proximity to forest areas (e.g., amenity is productive and $C_Q < 0$), $\frac{\partial p}{\partial Q} > 0$ and $\frac{\partial w}{\partial Q} \underset{>}{\overset{<}{-}} 0$. In equilibrium while the housing prices are higher in the location closer to forest amenities, the wage level can be higher or lower depending on the absolute value of the effects proximity to a forest amenity has on individuals' utility level and firms' costs (Wu and Gopinath 2008). On the other hand, if firms' costs increase with proximity to forest areas (e.g., amenity is unproductive and $C_Q > 0$), then $\frac{\partial p}{\partial Q} \underset{>}{\overset{<}{-}} 0$ and $\frac{\partial w}{\partial Q} < 0$. In particular, the empirical framework pursued in this paper adopts conventional assumptions for hedonic models: participants in the real estate and labor markets have full information about the relevant natural resource characteristics (Freeman 2003); housing and labor markets are in equilibrium; and the state of Arizona represents a single composite housing market. Since in this study reported household income (defined as HHINC) is used as a proxy for earned wages, HHINC instead of w is used throughout.

A plausible approach to estimate the left hand side of equation (3), 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

[6]In this analysis, it is assumed that the level of capital accumulation is constant across the state (e.g., differences in wages and housing prices are not a function of accumulated capital).

Freeman's (2003) theoretical hedonic price framework and using a vector notation, the price of a house depends on housing characteristics **S** (lot size, number of rooms, year built), neighborhood characteristics **N** (school quality, income level) and location-specific amenities **Q** (distance to forest views), such that for a house *i* in location *j*:

$$P_{ij} = P_{ij}(S_i, N_j, Q_{f,j}) \tag{5}$$

where the subscript *f* denotes the type of natural amenity included in the model. The vector **Q** includes road mile distance to four types of amenities: wilderness areas (WILD), national forest (FOREST), outstanding waters (WATER), and neighborhood parks (PARKS).[7] The coefficient of interest $\theta_f^{'}$ represents the effect of, for instance, road mile distance to WILD on housing prices (e.g., $\theta_{WILD} = \frac{\partial P_{ij}}{\partial Q_{WILD,j}}$). Without assuming any particular form, such as a Box-Cox transformation or log-linear specification, the econometric equivalent of equation (5) is:

$$P_{ij} = \alpha_0 + \beta' S_i + \varphi' N_j + \theta' Q_{f,j} + \varepsilon_i, \tag{6}$$

where $\varepsilon_i \sim N(0, \Omega)$, and β, φ, and θ are the coefficient vectors to be estimated. In this setting, while the disturbance ε_i is assumed to be normally distributed, its covariance matrix is of the general form Ω to account for heteroskedasticity and autocorrelation (e.g., off-diagonals are nonzero).

The partial derivative of Equation (4) is estimated in a similar manner. Building upon Mincer's (1974) wage equation, annual household income is a function of the household's

[7] To remind the reader, forest areas refer to lands under federal supervision, 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 rule R18-11-115.

human capital characteristics **HC** (education level, race, employment status), neighborhood characteristics **N**, and location-specific amenities **Q**, such that:

$$HHINC_{ij} = \gamma_0 + \eta' HC_i + \pi' N_j + \delta_f' \, Q_{f,j} + \mu_i, \qquad (7)$$

where $HHINC_{ij}$ is the annual income for household *i* in location *j*. It is important to note that since the main focus of this study is the effect of forest amenities on households' income, the *i* subscript represents household income and characteristics as opposed to a particular type of job (e.g., working conditions).

3.21 Spatial Econometrics

The model specification in equations (6) and (7) 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.[8] 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. As stated in Tobler's (1970) first law of geography: "everything is related to everything else, but near things are more related than

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[8] A second type of spatial effect that is not addressed in this model is spatial heterogeneity. This refers to spatial relationships for which the functional form requires parameters to vary with locations.

distant things" (Tobler 1970 pp. 236). 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, which is the case of this study (Anselin 1988).

Econometrically, spatial dependence can result in non-spherical disturbances (e.g., off-diagonal terms in the variance-covariance matrix of the disturbance vector are not all zero). In the context of this paper 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. Two different approaches can be implemented to address this issue: spatial lag and spatial error models. In the first approach, 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 and specified as:

$$P_{ij} = \alpha_0 + \rho W_1 P_k + \beta' S_i + \varphi' N_j + \theta' Q_{f,j} + \varepsilon_i, \forall \ i \neq k, \qquad (8)$$

where ρ is the spatial lag autoregressive coefficient, ε_i is a vector of spherical disturbance that are normally distributed, and W_1 is an *nxn* weight matrix that indicates how housing prices are related in space (e.g., the effect that a change in the price of house *k* has on the price of house *i*). This weight matrix represents a weighted average effect of housing prices in neighboring units and has non-zero elements w_{ik} when observations *i* and *k* are defined as neighbors. For house *i* in location *j*, this model is represented by the following expression:

$P_{ij} = \rho(w_{i1} p_1 + w_{i2} p_2 + w_{i3} p_3 ... + w_{in} p_n) + \psi' X + \nu_i$, where $w_{ii} = 0$ and $\rho \in [-1,1]$, $\psi = [\beta, \varphi, \theta_f]$ and $X = [S, N, \theta_f]$. Theoretically, a spatial lag model specification addresses the presence of biased outcomes stemming from spillovers across spatial units that vary with distance and location (Anselin 2001). If spatial dependence arises due to the omission of variables that are related in space, a spatial error model is appropriate (Anselin and Bera 1998).

In this case spatial dependence is introduced in the functional form of the error term and the specification of the housing price and wage equations are as follow:

$$P_{ij} = \alpha_0 + \beta' S_i + \varphi' N_j + \theta' Q_{f,j} + \mu_{i,house}, \quad (9)$$

with $\mu_{i,house} = \lambda_{house} W_2 \mu_{k,house} + \xi_{house}$,

$$HHINC_{ij} = \gamma_0 + \eta' HC_i + \pi' N_j + \delta'_f Q_{f,j} + \mu_{i,hhinc} \quad (10)$$

with $\mu_{i,hhinc} = \lambda_{hhinc} W_2 \mu_{k,hhinc} + \xi_{hhinc}$,

where λ_{house} and λ_{hhinc} are the spatial error autoregressive coefficients for the housing price and wage equations, respectively, and ξ_{house} and ξ_{hhinc} are vectors of spherical disturbance with zero mean.

Combining both types of lag processes in a single equation results in a more flexible specification to represent spatial relationships and could be appropriate when there is little or no theoretic support as to which spatial process should be introduced to address spatial autocorrelation. In this case, the general specification to represent the housing market is:

$$P_{ij} = \alpha_0 + \rho W_1 P_k + \beta' S_i + \varphi' N_j + \theta' Q_{f,j} + \mu_{i,house}, \quad (11)$$

with $\mu_{i,house} = \lambda_{house} W_2 \mu_{k,house} + \xi_{house}$,

where two different weight matrices are specified to address the identification problem that may arise if the same weight matrix is used to represent both spatial processes (Anselin 1980). In this analysis, the implicit marginal housing price (θ_f) and wage (δ_f) are estimated for each type of forest based on equations (11) and (10), respectively.

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 pre-defined and arbitrary. The lack of consensus and evidence regarding a suitable weight matrix 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[9]:

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

3.22 Empirical Estimation Process

Two plausible approaches can be used to estimate equations (10) and (11). One is a fully-simultaneous model in which the structural equations of housing demand, equation (11), and labor supply, equation (10), are estimated assuming error independence between equations. This restriction may not be appropriate if the error terms are correlated across equations. In this case, using a seemingly unrelated regression (SUR) approach that accounts for unobserved factors that affect the error terms in both equations would be suitable (Greene 2003). This is the approach this paper follows to estimate equations (10) and (11).

The SUR model with spatial error and lagged autocorrelation in the housing price equation and with a spatial error structure in the wage equation is estimated by applying a spatial Cochrane-Orcutt procedure analogous to that developed for the case with serial correlation in time series (Greene 2003). In the first step an Ordinary Least Square (OLS) and a 2-SLS regression are estimated for equations (10) and (11), respectively, without accounting for spatial

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[9] These weight matrices were created using RGui software.

error dependence.[10] In the second step, the residuals from the OLS regression $(\hat{\mu}_{1,hhinc}, \hat{\mu}_{2,hhinc}, ..., \hat{\mu}_{n,hhinc})$ are used to estimate λ_{hhinc} (the spatial error autoregressive coefficient of the wage equation) and the variance of the error term $(\sigma^2_{\xi,hhinc})$ using a GMM process outlined in Kelejian and Prucha (1999). In a similar fashion, the residuals from the 2-SLS regression $(\hat{\mu}_{1,house}, \hat{\mu}_{2,house}, ..., \hat{\mu}_{n,house})$ are used to estimate λ_{house} and the variance of the error term $(\sigma^2_{\xi,house})$ following Kelejian and Prucha (2004).[11] Using a general notation, λ_{wage}, $\sigma^2_{\xi,hhinc}$, λ_{house}, and $\sigma^2_{\xi,house}$ are estimated based on the following system of three equations:

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[10] The presence of a statistically significant spatial lagged coefficient (e.g., ρ) means that the estimated OLS coefficients in equation (11) would be biased and inefficient due to correlation or endogeneity problems between the lagged dependent variable (W_1P) and the error term (Anselin 1988). For this reason a 2-SLS approach is used with a vector of lagged independent variables (e.g., [WS WN WQ]) as instruments to obtain $\widehat{WP}$ in the first stage.

[11] Since a simultaneous system of equations was used in Kelejian and Prucha (2004), the following adjustments were made to estimate the SUR model: there is no direct dependency between housing prices and wages (e.g., a vector of housing prices is not included on the right hand side of the wage equation and vice versa) and that housing prices are not a function of the spatial lag of the independent variables included in equation (11) (e.g., only the spatial lag of other housing prices appears in equation 11).

$$(\hat{\mu}_{n,m} - \lambda_m W_2 \hat{\mu}_{n,m})'(\hat{\mu}_{n,m} - \lambda_m W_2 \hat{\mu}_{n,m}) - \sigma^2_{\xi,m} = \hat{\Phi}_{1,m}$$

$$\frac{(W_2 \hat{\mu}_{n,m} - \lambda_m W_2 W_2 \hat{\mu}_{n,m})'(W_2 \hat{\mu}_{n,m} - \lambda_m W_2 W_2 \hat{\mu}_{n,m})}{n} - \frac{1}{n} \sigma^2_{\xi,m} Tr(W_2' W_2) = \hat{\Phi}_{2,m} \quad (12)$$

$$\frac{(W_2 \hat{\mu}_{n,m} - \lambda_m W_2 W_2 \hat{\mu}_{n,m})'(\hat{\mu}_{n,m} - \lambda_m W_2 \hat{\mu}_{n,m})}{n} = \hat{\Phi}_{3,m}$$

where the subscript *m* refers to "hhinc" for equation (10) and "house" for equation (11), and $\hat{\Phi}_{1,m}$, $\hat{\Phi}_{2,m}$, $\hat{\Phi}_{3,m}$ are regression residuals. In this setting, the GMM estimators of λ_m and $\sigma^2_{\xi,m}$ ($\hat{\lambda}_m$ and $\hat{\sigma}^2_{\xi,m}$) are obtained from the minimization of the sum of the squared residuals or:

$$\min_{\lambda_m, \sigma^2_{1,m}} (\hat{\Phi}_{1,m} + \hat{\Phi}_{2,m} + \hat{\Phi}_{3,m}) \quad (13)$$

In the third step, $\hat{\lambda}_m$ allows for the estimation of the coefficients in equations (10) and (11) to account for spatial error autocorrelation.[12] This is achieved using the following spatial Cochrane-Orcutt transformed regression model[13]:

$$HHINC^*_{ij} = \gamma^t_0 + \eta'^t HC^*_i + \pi'^t N^*_j + \delta'^t Q^*_{f,j} + \mu^*_{i,hhinc}, \quad (14)$$

$$P_{ij} = \alpha^t_0 + \rho W_1 P^*_k + \beta'^t S^*_i + \varphi'^t N^*_j + \theta'^t Q^*_{f,j} + \mu^*_{i,house}, \quad (15)$$

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[12] In the first step, OLS and 2SLS approaches yield unbiased estimators. However, spatial error correlation within each equation was not taken into account, resulting in a loss of efficiency (Anselin 1988).

[13] Analogous to the case of time series with serial correlation, it can be shown that for this spatial Cochrane-Orcutt procedure the following equalities hold: $\eta'^t = \eta', \pi'^t = \pi', \delta'^t = \delta'$

$\eta'^t = \eta', \pi'^t = \pi', \delta'^t = \delta', \beta'^t = \beta', \varphi'^t = \varphi'$, and $\theta'^t = \theta'$ (Greene 2003).

where $HHINC^{*}_{ij} = HHINC_{ij} - \widehat{\lambda}_{hhinc} W_2 HHINC_{ij}$, $P^{*}_{ij} = P_{ij} - \widehat{\lambda}_{house} W_2 P_{ij}$, and

$Z^{*}_{ij,m} = Z_{ij,m} - \widehat{\lambda}_{m} W_2 Z_{ij,m}$ for $Z_{ij,m} = [HC_i \; N_{j,m} \; Q_{j,m}]$. Based on this transformation, a SUR model was estimated using the feasible generalized least squares method (Greene 2003). The different SUR models were compared based on McElroy's (1977) goodness-of-fit measure (McElroy R^2). The pair of weight matrices that yielded the highest McElroy R^2 value was 4KM (spatial lag) and IWD (spatial error).[14] For this reason, results reported in this paper have this weight matrix specification.

3.2 Data

In order to estimate the proposed spatial SUR model a matched sample of wage-earner housing units is used at the household level. In this sample, each observation includes reported household income (2006$), household characteristics (e.g., race, employment status), home value, and housing characteristics. In particular, the data for the housing and wage equations come from two different sources: 2007 survey for the Southwest Region in the United States 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 housing characteristics purchased from a commercial marketing vendor, PrimeraSource.[15] This

[14] For this specification, McElroy R^2 was 0.51 compared to 0.32 through 0.50 for the other 11 cases.

[15] The 2007 Region 3 Survey was conducted by The University of New Mexico Department of Economics in cooperation with the US Department of Agriculture Forest Service and the Rocky Mountain Research Station. This project involved a large general population sample, multi-mode

housing data was pursued after the final round of the 2007 Region 3 Survey was completed, since the objective was to obtain housing data for those who responded this survey. Thus, a matched sample of wage-earner housing units is used at the household level.

The sample for the wage equation is restricted to wage-earning households of 18 years of age and older. The characteristics for these households (e.g., income, education, race, employment status) were obtained from standard demographic questions included in the 2007 Region 3 Survey conducted by the University of New Mexico in conjunction with USDA Forest Service, Rocky Mountain Research Station (McCollum et al. 2008). Building upon the 1999-2000 USDA Forest Service National Survey on Recreation and the Environment (United States Forest Service, 2001), the 2007 Region 3 Survey was designed to provide input on individuals' values and objectives regarding land management of large public lands in the Southwestern Region (Arizona (AZ), New Mexico (NM), and small parts of Texas (TX) and Oklahoma, OK). The sampling includes a geographically stratified, random sample (with rural over-sampling for statistical purposes), which allows analysis at both the regional level, and for various sub-regional dis-aggregations (McCollum et al. 2008). This sample is comprised of 6,835 usable responses out of 7,626 received, from a sample frame of 37,804 (31,746) contacts, implying a response rate of 21.53 percent. For the purpose of this paper, this data was subsequently matched with housing data obtained from PrimeraSource. Since only few responses were received from

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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). Survey instrument constructed based on five focus groups held in the Economics Department at the University of New Mexico (McCollum et al. 2008).

the states of TX and OK and the housing information for NM had significant gaps (NM is a non-disclosure state, Berrens et al. 2006), this paper focuses on the state of AZ.[16] While 3,347 (2,998) usable survey responses were received from AZ, the following three issues did not allow the inclusion of all of them in this study: incomplete household demographic information, lack of housing information, household age higher than 64, household unemployed or homemaker, and no neighboring houses for the weight matrix defined as 3KM (e.g., closest home from house *i* is located further than the 3 kilometer threshold).[17] As a result, the estimates reported in this study are based on 1,014 observations.

A key issue in any study that uses survey data is the representativeness of the sample or subsample being used and the ability to weight the responses by known external data or variables to better represent target populations, if any biases are shown to exist (Champ, 2003). To address this issue, this study closely follows the sample weight methodology implemented for the 2007

[16] The breakdown of total responses received by state is: 3,509 for NM, 2,998 for AZ, 56 for OK, and 272 for TX.

[17] For Arizona, the number of non responses for the demographic section by characteristics are: 55 for gender, 30 for ethnicity (e.g., Hispanic/non-Hispanic), and 35 for years of education, 309 households were at least 65 years of age, and 40 were either unemployed or homemaker. Lack of housing information includes: 268 observations without any type of housing information, 289 without home values, 14 without year built, 612 without lot size, and 613 without total number of rooms. In addition, 68 observations without neighboring houses as defined by the 3KM weight matrix criterion had to be dropped.

Region 3 survey.[18] Given the nature of the sample, initial and post-stratification weights are used to ensure estimates that are representative of the population. The initial or survey weights are meant to ensure consistent estimates by reducing imbalances in the data (Dorofeev and Grant 2008). This initial weight is the product of two initial adjustments: a base weight and a non-response adjustment. The base weight is the inverse of the inclusion or selection probability, which is used to adjust survey estimates to reflect the population in the sample frame based on the sample design (Kneipp and Yarandi, 2002). The nonresponse adjustment, can be defined as, the number of responses divided by the sample, and controls for unit nonresponse or failure to achieve a 100% response rate (Lehtonen and Pahkinen, 2004). Therefore, initial weights compensate for unequal sampling rates and unit non-response.

Certain personal or demographic characteristics of the sample are not known until after data is collected, but if known in advance could have led respondent to be further stratified in the sample plan. Post-stratification allows for stratification of the sample after data has been gathered (Cochran, 1977). These demographic characteristics are known after data has been collected. As reported in Table 1, both men and high income households tend to be overrepresented in this sample. The mean household age is 54 compared to 43 for the true population. In terms of race, it has a greater proportion of whites than indicated for the population. Based on these comparisons, post-stratification weights were estimated based on four demographic factors: age, race, income and educational attainment. The final weights are the product of initial and post-stratification weights. They control for unequal sampling probabilities

[18] In the 2007 Region 3 survey, weights were constructed at the regional level (sample data was divided in 12 regions) and at the county level. Since the market area studied in this paper is comprised by one state, Arizona, county sample weights are used to adjust the data.

and non-response (initial weights) and adjust the data for uneven proportions between sample and population (post-stratification weights). As can be seen in Table 1, when using weights, the difference between the sample and the population is significantly reduced. For instance, the weighted proportion of males and whites is 52 percent and 78 percent compared to 50 percent and 82 percent for the population, respectively.

The dependent variables are LNINC, 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 weighted mean household income is $54,621 and the mean home value is $166,019 in 2006$.[19] 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.[20]

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

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[19] The weighted mean value for home values is $177,308. Since the year home values were assessed was in 2008, the price in 2006 dollars is $166,019 given a Consumer Price Index conversion factor of 1.068.

[20] The State of New Mexico is excluded in this study given the large number of missing values for housing data obtained from PrimeraSource.

The variables that measure forest characteristics are logged road mile distance from house *i* to its closest forest land under federal supervision (LNFOREST, includes wilderness areas), and Congressionally-designated wilderness area (LNWILD). These areas are expected to be an amenity (e.g., $\theta_f < 0$ in the housing equation and $\delta_f > 0$ in the wage 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 natural amenities used in estimation include closest logged distance to outstanding water (LNWATER), to neighborhood parks (LNPARKS) and logged distance to a landfills (LNLANDFILL).

The independent variables for the housing-price equation include the number of room (ROOMS), 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). The wage 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). Table 3 describes these variables, and provides descriptive statistics.

3.3 Empirical Results

The presence of both spatial lag and error processes in the housing market as specified in equation (11) may have a number of reasons. Housing prices may not only be determined by its particular characteristics (such as lot size or year built) but also by prices in neighboring houses, resulting in spatial spillover effects that require the inclusion of a spatially lagged dependent variable in the model. Moreover, it is realist to assume that not all the factors affecting housing prices are quantifiable or included in this model. For this reason a spatial error structure may also be needed to obtain reliable results.

Econometrically, these prior beliefs about the nature of spatial dependence can be tested using a series of diagnostics tests. A well known and commonly used test statistic is the Moran's I, 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). An alternative is the Lagrange Multiplier test (LM) derived by Anselin (1988) that allows for testing residual spatial error autocorrelation in the presence of a spatially lagged dependent variable ($LM_{\lambda/\rho}$) and vice versa ($LM_{\rho/\lambda}$). 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 λhouse = 0 as outlined in Anselin (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 ρ = 0. The LM tests have a chi-squared (χ^2) distribution with one degree of freedom (e.g., the restriction that λ = 0 or ρ = 0).

Tables 4 and 5 report the $LM_{\lambda/\rho}$ and $LM_{\rho/\lambda}$ values. In almost all cases, the χ^2 values are significant at a 99 percent confidence level. For instance, when the pair of weight matrices is $IWD_{1.5}$ (spatial lag) and $IWD_{1.0}$ (spatial error), spatial lag autocorrelation is statistically significant after controlling for spatial error dependence (29.65 for WILD and 32.24 for forest). These findings suggest that in order to obtain reliable estimates, the general specification of spatial dependence defined in equation (11) for the housing equation is required.

3.41 SUR Results

To determine the functional form of the dependent and independent variables in the housing equation, a Box-Cox specification was tested and the coefficients by which the variables would have to be transformed were close to zero and statistically insignificant ($\lambda_{IRAS}^{BoxCox} = 0.07, \lambda_{WILD}^{BoxCox} = 0.06,$ and $\lambda_{FOREST}^{BoxCox} = 0.09$). For this reason, a log form was chosen for both the dependent variables (housing prices) and for the natural amenity distance variables. In the case of the wage equation, since many of the independent variables are categorical (e.g., zero or one value), a log form is specified for the dependent variable (household income).

The spatial SUR models for equations (10) and (11) are estimated and reported in Table 6. The residual correlation of 0.12 for IRAS, 0.13 for WILD, and 0.14 for Forest are all statistically significant at a 99 percent confidence level, supporting the use of a SUR approach.

The estimates for the structural characteristics and the household's human characteristics for the housing and wage equations are all statistically significant and have the expected signs. For instance, home values increase with lot size, number of rooms, and year built (e.g., the more recent the house was built the higher its value). Household wages vary significantly depending on years of education, gender (household males tend to earn higher wages compared to females), and race (Whites, the base case, earn significantly higher wages than Blacks and households with two races).

The spatial lag autocorrelation coefficient (ρ) ranges between 0.47 and 0.52 and is statistically significant at across all level models, indicating that home values are positively related. This result underscores the importance of accounting for spatial dependence. However, in this spatial SUR approach, inferences about the significance of the error autocorrelation coefficients (λ_{wage} or λ_{house}) are not possible. Since these coefficients are estimated in step 2 of this 3-step process using GMM, their t-values from the SUR regression (the last step) are not identifiable. While it is not possible to make any conclusions about the joint significance of a spatial lag and error processes in this SUR model, the LM tests reported in Tables 4 and 5 suggest the need to include both types of spatial dependences.

The coefficients for WILD and FOREST support the hypothesis that these different types of forest areas are amenable to 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 wages for forest area as indicated by the positive coefficients for these variables (e.g., the closer a household lives from a forest area, the lower his annual wage). A similar relationship is found for the other natural amenities included in the model. For instance, households are willing to earn a lower wage for living closer to lake areas or outstanding waters and home values increase the closer a house is located from these amenities.

In the case of the other geographic features, results indicate that housing prices and wages increase the closer a household lives from an urbanized area (defined as a territory with 50,000 or more individuals). Landfill sites (LNLANDFILL) have a statistically significant effect (negative for housing prices and positive for wages) except for the equation in which the type of forest included is national forest. It is worth noting that conclusions about the effect of each geographic feature on home values and household income based on simply comparing coefficients across equations may lead to inaccurate conclusions. While the absolute values of these coefficients are in most cases higher for the wage equation, the presence of spatial processes requires calculations of total implicit prices to have a proper understanding of their magnitude.[21] By means of this empirical exercise, it is possible to estimate in monetary terms, for instance, how much of the value that individuals have for living in the proximity to forest areas is capitalized in the housing and labor markets (e.g., implicitly paying a higher house price and earning a lower wage). The variables of interest in this analysis are forest areas.

The first step to calculate total implicit prices is to derive the marginal effects for each market separately. Following Freeman's (2003) theoretical hedonic framework, applying total differentiation to the indirect utility function or equation (1) gives the following expression, which represents the individuals preference for access to forest areas at the margin:

$$\frac{V_{Q_f}}{V_{HHINC}} = -\frac{V_p}{V_{HHINC}}\frac{dp}{dQ_f} - \frac{dHHINC}{dQ_f} \qquad (16)$$

where HHINC is used instead of w to reflect the level of income data used in this analysis. In this equation, it is assumed that the market is in equilibrium or $dV = 0$ (e.g., same utility level ($\bar{V}$) across all locations). Since at equilibrium individuals trade proximity to forest areas for wages, $\frac{V_{Q_f}}{V_{HHINC}}$ represents the marginal rate of substitution between the forest variable (Q_f) and the numeraire good (e.g., income spent in all market goods consumed). Assuming that the same individual does not own more than one house and using Roy's identity yield the following total implicit price expression for the Q_f:

$$P_{Q_f} = \frac{dp}{dQ_f} - \frac{dHHINC}{dQ_f} \qquad (17)$$

[21] It is also important to note that the housing equation is specified with both spatial processes (spatial lag and error) while only spatial error dependence is included in the wage equation.

where $\frac{dp}{dQ_f}$ and $\frac{dHHINC}{dQ_f}$ are the partial derivates of equations (14) and (15) that indicate how home prices and household income change with changing proximity to forest areas. Based on the Cochrane-Orcutt transformation in step 3 for estimating the spatial SUR model, equations (14) and (15) can be rewritten as:

$$(I-\lambda_{house}W_2)(I-\rho W_1)P_{ij} = (I-\lambda_{house}W_2)\beta'^{t}S_j + (I-\lambda_{house}W_2)\varphi'^{t}N_j + \tag{18}$$

$$+(I-\lambda_{house}W_2)\theta'^{t}Q_{f,j} + \xi^{*}_{i,house}$$

$$(I-\lambda_{house}W_2)HHINC_{ij} = (I-\lambda_{hhinc}W_2)\eta'^{t}HC_j + (I-\lambda_{hhinc}W_2)\pi'^{t}N_j + \tag{19}$$

$$+(I-\lambda_{hhinc}W_2)\delta'^{t}Q_{f,j} + \xi^{*}_{i,hhinc}$$

Assuming a log form for both dependent variables ,and for the natural amenity distance variables, the right hand side expressions in equation (17) are found by taking the partial derivate in the above equations with respect to $Q_{f,j}$ (forest characteristic): WILD, or FOREST[22]:

$$\frac{dp}{dQ_f} = (I-\rho)^{-1}\theta'^{t}\,\frac{Q_{f,j}}{P_{ij}} \tag{20}$$

$$\frac{dp}{dQ_f} = \delta'^{t}\,\frac{Q_{f,j}}{HHINC_{ij}} \tag{21}$$

In equation (20), two types of effects are estimated: the direct-contemporaneous effect and indirect effects. The first effect refers to how the price of home *i* changes with proximity to a given forest characteristic. Indirect effects represent the impact on home price *i* of changes in the

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[22] Since the spatial weight matrices are row-standardized (e.g., each row adds up to one), the partial derivative in equation (3.20) assumes the following equality: $(I-\rho W_1)^{-1} = (I-\rho)^{-1}$.

price of neighboring home j due to its distance to, for instance, wilderness lands (represented by ρ).

The annualized marginal effect estimates using the above equations are reported in Table 6 for the presence of different forest characteristics, water and parks. Evaluated at the mean house price of $165,128 and mean household income of $45,175, the average home price increases by $380 and the average household income decreases by $316 for moving one mile closer to wilderness areas, given an initial distance of 30 miles (the mean for the sample). The resulting total implicit price is $696 per mile. When measured by proximity to forest areas and protected waters, total implicit prices are $1,090 and $527, respectively. Since forest areas refer to all lands under federal supervision, including wilderness lands, it is reasonable that the implicit value for the inclusive amenity (FOREST) is larger than that for the subset good (wilderness).

Total implicit price for neighborhood parks is $8,003 per mile. While this feature appears to be more "more expensive" on the margin, it is important to note that for a house the average closest distance from a park is 1.6 miles, compared to 25 and 30 miles for wilderness and forest areas. This may partially explain the significant difference in total implicit prices between these geographic features. For instance, if the average distance to a forest area (25 miles) is assumed as the average closest distance to a park, the total implicit value would be $522 rather than $8,003, which is shown in Figure 1. As expected, the effect of these natural amenities on the housing and labor markets can be represented by a distance decay function.

3.4 Conclusion

This study has examined the role of natural amenities, such as protected lands (wilderness), neighborhood parks, and protected waters as determinants of spatial variations in housing prices and wages for the State of Arizona. In particular, the presence of off-site benefits, one type of the total economic value of forest lands, suggest that individuals' preferences for housing and job location is 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 forest amenities is not simply as intermediate goods in the production process, such as logging. In a regional study, Hand et al. (2008) empirically show that wilderness and U.S. Forest Service (USFS) areas carry implicit prices in the housing and labor markets that range between $27 and $85 per square mile annually in the Southwest United States (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 non-market benefits that such amenities may offer (Loomis and Richardson 2000; Berrens et al. 2006). As it is the case in other studies, this paper reports estimates based only on an "instrumental" value concept, which assumes that the value of these amenities is only a function of their usefulness in satisfying human needs (Tietenberg and Lewis 2011). For instance, in the case of forest lands, empirical evidence shows that intrinsic values (such as passive use values) may represent a significant percentage, and sometimes a majority proportion, of the total economic value associated with protected forest areas in the U.S. (Loomis 1996).

After controlling for housing, neighborhood, household's human capital characteristics and location specific amenities, results show that the average total implicit price for forest land under federal supervision is $1,091 per mile compared to $696 for wilderness areas per mile, annually. These values are based on a Geographic Information System (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 wage differentials suggest that individuals' are choosing where to live partially based on proximity to natural amenities. As a result, monetary evaluation techniques, such as the travel cost method, would not reflect the full price of recreation site access, and may lead to underestimates of such values and reveal an implicit value that is lower than individuals' willingness to pay Schmidt and Courant (2006).

The underlying spatial relationships among observations were determined by applying Lagrange Multiplier (LM) tests for the co-existence of spatial lag and spatial error processes. The econometric approach applied in this study follows Kelejian and Prucha (2004) to test the empirical question of whether there are strong amenity effects in the housing and labor markets. The SUR model with spatial error and lagged autocorrelation in the housing price equation and with a spatial error structure in the wage equation is estimated by applying a spatial Cochrane-Orcutt procedure analogous to that develop for the case with serial correlation in time series (Greene 2003). As expected, all spatial lag autocorrelation coefficients are statistically significant and positive, confirming the existence of spatial lag effects. However, while LM tests indicate that spatial error autocorrelation is present after controlling for spatial lag dependence, the significance of the spatial error coefficients (e.g., λ_{house} and λ_{hhinc}) is not identifiable in the SUR estimation process.

The zone effect or ecological fallacy observed in other studies is mitigated 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, since the level of observation are households identified to geocoded points on a map, 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.

Furthermore, 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. Since the presence of natural amenities may in part explain net migration patterns, such an assumption could be too restrictive.

Table 1: Weighted and Census Data Comparison

	Survey (unweighted, 2007)	Survey (weighted)	U.S. Census (2000)
HH Mean Income	$83,799	$45,176	$53,591
Mean Age	51	41	45
Gender	Male (72%) Female (28%)	Male (52%) Female (48%)	Male (50%) Female (50%)
Race	White (95%) Asian (1%) Black (1%) American Indian (1%) Native Hawaiian (0.2%) Two or more races(2%)	White (78%) Asian (5%) Black (4%) American Indian (3%) Native Hawaiian (0.2%) Two or more races(3%)	White (82%) Asian (2%) Black (3%) American Indian (4%) Native Hawaiian (0.1%) Two or more races(2%)
Education	High School or Less (11%) Some College (33%) Bachelor Degree (28%) Grad or Prof. Degree (28%)	High School or Less (61%) Some College (23%) Bachelor Degree (12%) Grad or Prof. Degree (4%)	High School or Less (43%) Some College (33%) Bachelor Degree (15%) Grad or Prof. Degree (8%)

Note: Median household for the U.S. 2000 Census was 40,588 (in 1999 dollars). Using a consumer price index conversion factor of 0.826, median household income in 2006$ is $49,102.

Table 2: Definitions and Weighted 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, US Bureau of the Census)	3.58	2.99
LNURBAN	Distance to nearest urbanized area, miles (GIS, US Bureau of the Census)	6.67	3.02
LNPARK	Distance to nearest neighborhood park, miles (GIS, US Bureau of the Census)	1.63	1.41
LNHIGHWAY	Distance to nearest highway, miles (GIS, US 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/Protected 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.shtml and http://roadless.fs.fed.us.
ADEQ: Arizona Department of Environmental Quality, US Bureau of the Census, and US Department of Commerce, http://agic.az.gov/portal/dataList.do?sort=theme&dataset=54.

Table 3: Definitions and Weighted Descriptive Statistics of Housing and Wage Variables

Variable	Definition		
Housing variables		Mean	Std. Dev.
LNHVALUE	House sale value (2007 $)	165,128	85,706
ROOMS	Total number of rooms	5.56	1.22
HAGE	Age of a house (2007 - year built)	31.53	16.06
LOTSIZE	Size of a house (acres)	0.20	0.30
Wage variables			
LNINC	Annual Household income (2007 $)	45,176	28,497
EDUC	Years of education	5.55	1.50
EXP	Years of working experience	21.82	15.61
EXP2	Years of working experience squared	719.47	999.03
WORKPT	1 = work part-time, 0 else	0.11	0.31
RETIRED	1 = retired, 0 else	0.14	0.35
HOMEMAKER	1 = homemaker, 0 else	0.32	0.47
STUDENTFT	1 = full-time student, 0 else	0.05	0.21
STUDENTPT	1 = part-time student , 0 else	0.001	0.05
ACTIVEMIL	1 = Active duty U S Armed Forces, 0 else	0.002	0.00
RESMIL	1 = Military Reserve or National Guard, 0 else	0.003	0.01
UNEMPL	1 = Unemployed looking for a job, 0 else	0.03	0.22
TWORACES	1 = Two or more races, 0 else	0.05	0.46
ASIAN	1 = Asian/Pacific islander, 0 else	0.01	0.05
BLACK	1 = Black, 0 else	0.00	0.05
AMERINDIAN	1 = Native American/Alaska Native, 0 else	0.01	0.02
HAWAIIAN	1 = Hawaiian, 0 else	0.002	0.04
MALE	1 = Male, 0 else	0.52	0.47
LIVINGNRE	1 = 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), 0 else	0.05	0.16

Table 4: Lagrange Multiplier Diagnostics For Housing Equation

	Spatial error autocorrelation in the presence of spatial lag					
Weight Matrix						
Spatial lag	$IWD_{dist1.5}$	$IWD_{dist1.5}$	$IWD_{dist1.5}$	$IWD_{dist1.0}$	$IWD_{dist1.0}$	$IWD_{dist1.0}$
Spatial error	$IWD_{dist1.0}$	4KM	3KM	$IWD_{dist1.5}$	4KM	3KM
Open Space Variable						
Wilderness	31.20***	27.52***	30.13***	25.96***	34.43***	20.17***
Forest	29.14***	38.74***	20.10***	26.88***	30.45***	23.21***

	Spatial error autocorrelation in the presence of spatial lag					
Weight Matrix						
Spatial lag	4KM	4KM	4KM	3KM	3KM	3KM
Spatial error	$IWD_{dist1.5}$	$IWD_{dist1.0}$	3KM	$IWD_{dist1.5}$	$IWD_{dist1.0}$	4KM
Open Space Variable						
Wilderness	24.68***	39.51***	15.71***	12.41***	25.12***	5.34***
Forest	29.89***	23.04***	11.84***	10.07***	37.22***	8.17***

Table 5: Lagrange Multiplier Diagnostics For Housing Equation

	Spatial lag autocorrelation in the presence of spatial error					
Weight Matrix						
Spatial lag	$\text{IWD}_{dist1.5}$	$\text{IWD}_{dist1.5}$	$\text{IWD}_{dist1.5}$	$\text{IWD}_{dist1.0}$	$\text{IWD}_{dist1.0}$	$\text{IWD}_{dist1.0}$
Spatial error	$\text{IWD}_{dist1.0}$	4KM	3KM	$\text{IWD}_{dist1.5}$	4KM	3KM
Open Space Variable						
Wilderness	29.65***	5.06***	6.92**	10.45***	7.82**	6.88***
Forest	32.24***	11.43***	8.50***	16.29***	13.51***	4.50**

	Spatial lag autocorrelation in the presence of spatial error					
Weight Matrix						
Spatial lag	4KM	4KM	4KM	3KM	3KM	3KM
Spatial error	$\text{IWD}_{dist1.5}$	$\text{IWD}_{dist1.0}$	3KM	$\text{IWD}_{dist1.5}$	$\text{IWD}_{dist1.0}$	4KM
Open Space Variable						
Wilderness	10.11***	64.30***	25.01***	11.91***	82.47***	13.93***
Forest	16.20***	31.05***	12.45***	19.28***	8.30***	10.52***

Table 6: Estimation Results, Weighted SUR Models

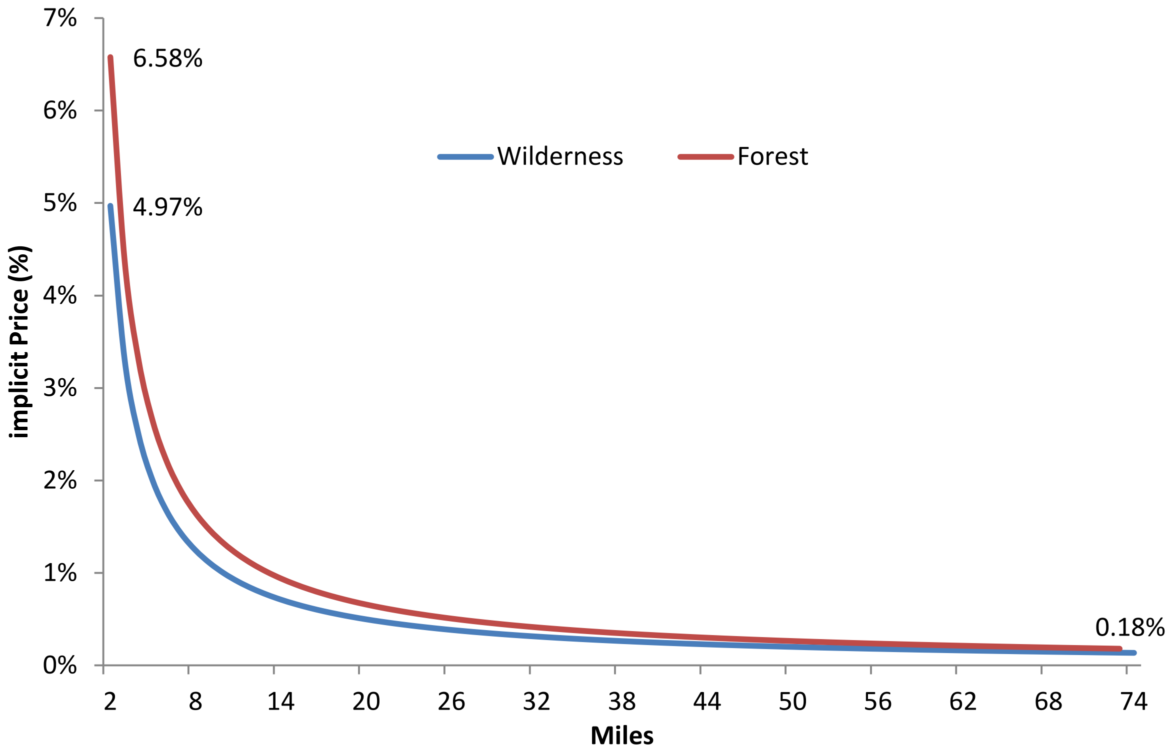
	Housing	Wage
ROOMS	0.10***	
HAGE	-0.01***	
LOTSIZE	0.21***	
LNHIGHWAY	-0.05**	
LNHOSPITAL	0.001	
LNGOLF	-0.02	
EXP		0.01**
EXP2		-0.0001*
EDUC		0.08***
WORKPT		-0.63***
RETIRED		-0.39***
HOMEMAKER		-0.21***
STUDENTFT		-0.03*
STUDENTPT		-0.23
ACTIVEMIL		-1.74
RESMIL		-0.41
UNEMPL		-0.40***
TWORACES		-0.21***
ASIAN		0.76***
BLACK		-0.28***
AMERINDIAN		-0.67***
HAWAIIAN		-0.13
MALE		0.10**
LIVINGNRE		0.15**
LNWILD	-0.04**	0.21**
LNFOREST	-0.05**	0.40***
LNSPFUND	0.13***	0.42***
LNURBAN	-0.06***	-0.12***
LNWATER	-0.06**	0.76***
LNPARK	-0.03**	0.11**
ρ	0.29***	
λ	0.36	0.67
McElroy R^2	0.47	
N	1,885,059	
Residu. Corr	0.12	

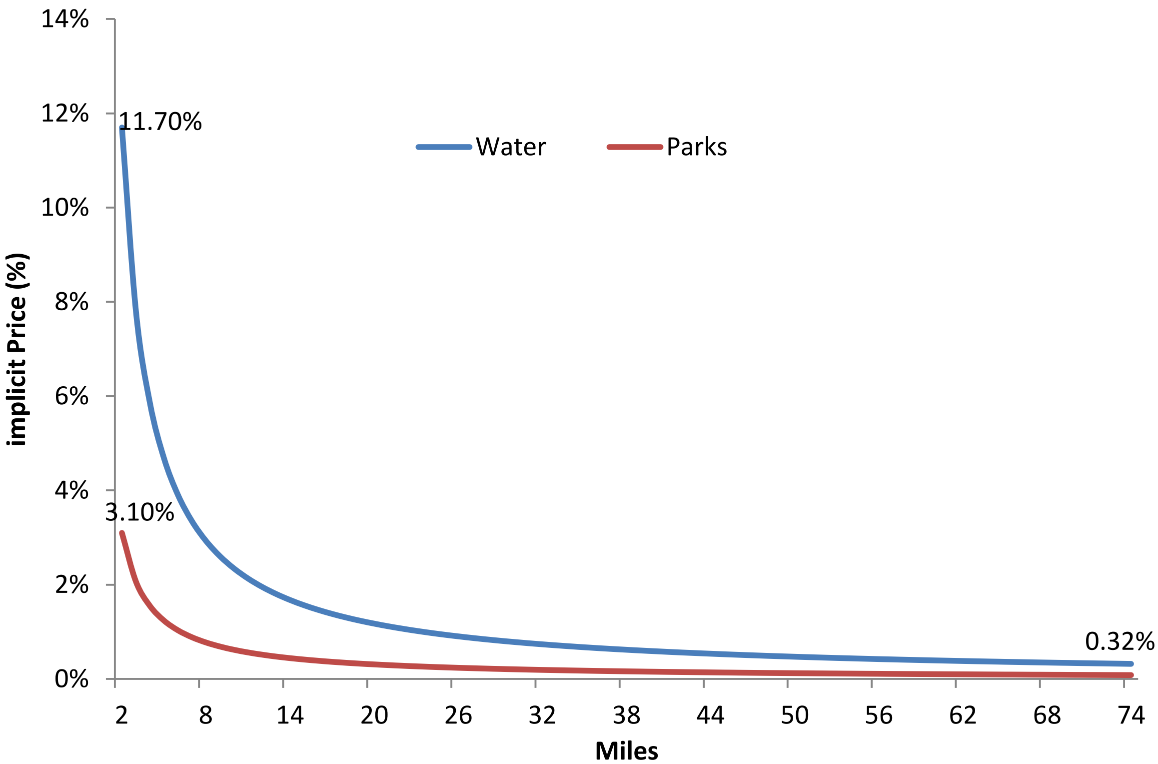
*, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 7: Total Implicit Values ($)

	$\partial P/\partial Q$	$\partial HHINC/\partial Q$	Total Implicit Price (P_Q)
National Forest	0.23%	0.70%	0.93%
Wilderness	0.19%	0.36%	0.56%
Water	0.30%	2.52%	2.82%
Parks	0.16%	0.37%	0.53%

Figure 1: Total Implicit Prices





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