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Recovering Marginal Willingness to Pays from Hedonic Prices under Imperfect Competition

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Recovering Marginal Willingness to Pays from Hedonic Prices under Imperfect Competition

Abstract

In this paper, hedonic price analysis under imperfect competition is studied. We demonstrate a means to simultaneously recover the price-cost markup and the marginal values of product attributes from hedonic price estimation under imperfect competition. Our theoretical results provide guidance to the empirical specification of the hedonic price model, increasing both the applicability and reliability of hedonic valuation methods. We conduct a Monte Carlo simulation to evaluate various specifications of hedonic price models under imperfect competition. An application to estimating marginal willingness to pays for characteristics of a ski resort is presented.

JEL code: Q51, L10

Key Words: Hedonic Method, Imperfect Competition, Taxation, Price-Cost Markup, Monte Carlo Simulation

1. Introduction

This study is motivated by an issue that is often overlooked in empirical hedonic price analysis: the effects of market power. We extend the theoretical framework of Feenstra (1995) to incorporate taxation in the hedonic model under imperfect competition and show that taxation affects the equilibrium price both directly and indirectly through its interaction with other product characteristics. Importantly, the inclusion of the tax variables provides a feasible means of estimating the price-cost markup to help recover the marginal values of product attributes from the hedonic price model under imperfect competition.

The seminal paper by Rosen (1974) provides the theoretical foundation for the modern empirical hedonic price analysis of differentiated products. Under the assumption of pure competition, Rosen shows that the equilibrium price locus of a differentiated product is a collection of tangent points between bid and offer curves. Therefore, partial derivatives of the hedonic price function, with respect to the product attributes, are equivalent to the marginal values of these attributes. Numerous environmental valuation applications employ Rosen's results to empirically recover the marginal willingness to pay for environmental quality (e.g., Smith and Huang, 1995).

In a market of differentiated products, pricing above marginal costs is possible with the presence of market power. Feenstra (1995) extends Rosen's framework to imperfect competition and shows that when there exists a price-cost markup, and when the underlying cost structure and utility functions do not translate to a linear hedonic price equation, the price-cost markup is embedded in the coefficient of each attribute. Consequently, the partial derivatives of the equilibrium hedonic price equation do not directly represent marginal values of product attributes. The inseparability, of the price-cost markup and the marginal values of product

attributes in the non-linear hedonic price equation, presents empirical difficulty of employing the hedonic method for environmental valuation under imperfect competition.

There has been limited research in the empirical implementation of hedonic method under imperfect competition, despite the fact that price-cost markup can potentially be significant in a market of differentiated products. A few empirical studies utilize Feenstra's theoretical results and employ a two-step approach to first estimate the price-cost markup for each firm in an imperfectly competitive market via the residual demand estimation with external data, then use it to help recover the marginal values of product attributes from the estimated hedonic price equation (Taylor and Smith (2000) and Oktem and Huang (2011)). The estimation of residual demand models requires extra data collection and additional assumptions of the demand facing the firms.

The other focus of this study is the role of taxation in the equilibrium hedonic price model. For example, empirical evidence of tax capitalization into property values has been well documented in the literature (e.g., Gyourko and Tracy (1991), Chattopadhyay (1999), Chay and Greenstone (2005)). The tax variables are frequently omitted in the estimation of hedonic housing price equations, mainly because the majority of property value studies for environmental valuation utilize data within one jurisdiction where there is no or insufficient variation in tax rates. In larger scale studies with multiple cities, tax variables can be included but they are often treated as additional attributes in hedonic price models. This approach may not be fully consistent with economic theory, especially when the market is imperfectly competitive as demonstrated in the next section.

The analysis in this paper offers insights to the empirical specification of hedonic price models with taxation under imperfect competition, showing that tax variables enter the price

equation directly and indirectly through interactions with the product attributes. Our theoretical results provide a means to directly recover the price-cost markup from the estimation of the hedonic price equation that enables convenient estimation of the marginal values of product attributes. These results enhance the proper use of hedonic method for non-market valuation when the market is imperfectly competitive and when taxes are present.

2. Equilibrium Hedonic Prices, Taxation, and Price-Cost Mark up

Consider product i that is differentiated by a vector of characteristics $\mathbf{z}_i \in R_+^K$. Feenstra (1995) shows that, when marginal product costs are log-linear (a.k.a. semi-log) in product characteristics, the marginal cost of characteristic k in product i , $\frac{\partial C_i(\mathbf{z}_i^*)}{\partial z_{ik}}$, is equal to a fraction of its marginal value, $\frac{\partial \pi_i(q_i^*, \mathbf{z}_i^*)}{\partial z_{ik}}$, that the fraction is affected by the price-cost markup, $\frac{P_i^* - C_i(\mathbf{z}_i^*)}{P_i^*}$, and the elasticity of substitution between the quality adjusted prices (q) and characteristics, σ_{ik} .

$$\frac{\partial C_i(\mathbf{z}_i^*)}{\partial z_{ik}} = \frac{\partial \pi_i(q_i^*, \mathbf{z}_i^*)}{\partial z_{ik}} \times \left[1 - \left(\frac{P_i^* - C_i(\mathbf{z}_i^*)}{P_i^*} \left(\frac{1}{\sigma_{ik}} \right) \right) \right], \text{ where } P_i = \pi_i(q_i, \mathbf{z}_i). \quad (1)$$

In the above equation, the (*'s) represent equilibrium levels of choice variables and q_i denotes the quality-adjusted price as a function of P_i and \mathbf{z}_i , $q_i = \phi(P_i, \mathbf{z}_i)$. Equation (1) indicates that the coefficients of the characteristics in the hedonic price equations may not represent their marginal values when there exists a price-cost markup. Consequently the resulting price equation can be approximated as follows (Feenstra (1995)).

$$\ln P = \alpha + \left(\frac{P}{C} \right) \beta' \mathbf{z} + v \quad (2)$$

The coefficients of each characteristic consist of two components: the marginal value of the characteristic, represented by β , and the price-cost ratio, $\left(\frac{P}{C} \right)$. When market power is not

accounted for, the coefficients in the estimated hedonic price equation will be biased upward by the amount of the unknown price-cost markup.

In this study, we extend Feenstra's framework to incorporate taxes levied on consumers and producers in an imperfectly competitive market. Taxes can be imposed on either consumers or producers or both. Suppose that taxes T^b and T^s are imposed on consumers and producers, respectively. For example, T^b can be a sales tax that is itemized and added on top of the ski lift ticket price at the time of purchase to be paid by consumers; T^s can be a property tax that is levied on a home owner (seller), but it is often fully or partially capitalized into the sale price received by the seller. Note that it is not necessary and in fact less common to have both T^b and T^s in an empirical study. We incorporate both T^b and T^s in the theoretical derivations so the results are applicable to either type of taxes.

Let P_i be the price of product i charged by producers, e.g., P is the price of a lift ticket at a ski resort. The total price of product i paid by consumers, denoted \tilde{P}_i , is equal to $P_i(1 + T^b)$, and the actual price received by producers after taxes is equal to $P_i(1 - T^s) = \tilde{P}_i \frac{1 - T^s}{1 + T^b}$. Then, the profit maximization of a firm selling multiple product varieties can be described as follows.

$$\max_{P_i, \mathbf{z}_i} \sum_{i=1}^n \left[\tilde{P}_i \frac{1 - T^s}{1 + T^b} - C_i(\mathbf{z}_i) \right] X_i(\tilde{P}_i, \mathbf{z}_i; \tilde{P}_{-i}, \mathbf{z}_{-i}) \quad (3)$$

X_i is the expected market demand for product i , given the prices (\tilde{P}_{-i}) and the characteristics (\mathbf{z}_{-i}) of other products. C_i denotes the cost of producing one unit of product i , which is an increasing function of the characteristics of the product. The choice variables to maximize the

firm's profit are the prices of products paid by consumers (\tilde{P}_i) and the bundle of characteristics (\mathbf{z}_i) for each product.¹

Rewrite the market demand by deriving it from the social welfare function. The social welfare function is necessarily an aggregate indirect utility function given as $V(\cdot)$. Following McFadden (1978), we have:

$$X_i = -\frac{\partial V_i / \partial \tilde{P}_i}{\partial V_i / \partial Y} = -\frac{\partial \phi_i}{\partial \tilde{P}_i} \frac{\partial V / \partial \phi_i}{\partial V / \partial Y} = -\left(\frac{\partial \tilde{\pi}}{\partial q_i}\right)^{-1} \frac{\partial V / \partial \phi_i}{\partial V / \partial Y} \quad (4)$$

Let $(\tilde{P}_i^*, \mathbf{z}_i^*)$ be the Nash Equilibrium at which the profits of the firms are maximized and let $q_i^* = \phi(\tilde{P}_i^*, \mathbf{z}_i^*)$ be the quality adjusted price of product i that holds utility constant. By inverting the quality adjusted price function, we obtain $\tilde{P}_i = \tilde{\pi}_i(q_i, \mathbf{z}_i)$.

Since $V(\cdot)$ is a function of quality-adjusted prices and income, the demand for other products will be held constant given $q_i = q_i^*$. In other words, the value of $\frac{\partial V / \partial \phi_i}{\partial V / \partial Y}$ evaluated at q_i^* will not be affected by any choice of \mathbf{z}_i . Then, Equation (3) can be rewritten as a sub-problem of profit maximization for each product i .

$$\max_{\mathbf{z}_i} \left[\tilde{\pi}_i(q_i^*, \mathbf{z}_i) \frac{1 - T_i^s}{1 + T_i^b} - C_i(\mathbf{z}_i) \right] \left(\frac{\partial \tilde{\pi}_i(q_i^*, \mathbf{z}_i)}{\partial q_i} \right)^{-1} \quad (5)$$

The transformed objective function now only has one set of choice variables which is the vector of characteristics of product i . The first-order conditions for the maximization of (5) are:

$$\frac{\partial C_i(\mathbf{z}_i^*)}{\partial z_{ik}} = \frac{\partial \tilde{\pi}_i(q_i^*, \mathbf{z}_i^*)}{\partial z_{ik}} \frac{1 - T_i^s}{1 + T_i^b} \left(1 - \left(1 - \frac{1 + T_i^b}{1 - T_i^s} \frac{C_i(\mathbf{z}_i^*)}{\tilde{\pi}_i(q_i^*, \mathbf{z}_i^*)} \right) \frac{1}{\sigma_{ik}} \right) \quad (6)$$

$$\text{where } \sigma_{ik} = \left(\frac{\partial \tilde{\pi}_i(q_i^*, \mathbf{z}_i^*)}{\partial z_{ik}} \right) \left(\frac{\partial \tilde{\pi}_i(q_i^*, \mathbf{z}_i^*)}{\partial q_i} \right) \left(P_i^* \frac{\partial^2 \tilde{\pi}_i(q_i^*, \mathbf{z}_i^*)}{\partial q_i \partial z_{ik}} \right)^{-1}$$

¹ Feenstra (1995) discussed various conditions examined in Caplin and Nalebuff (1991) and Milgrom and Roberts (1990) to guarantee the existence of a pure-strategy Nash equilibrium.

In the above equation, σ_{ik} gives the elasticity of substitution between q_i and z_{ik} evaluated at (q_i^*, \mathbf{z}_i^*) .

The assumption of functional form of the cost function determines the empirical specification of the hedonic function. Suppose that the cost function has a semi-log form.

$$\ln C_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} + v_i \quad (7)$$

By adding $\ln \tilde{P}_i$ and subtracting $\ln C_i$ on both sides of (7), the hedonic price model can be written as follows.

$$\ln \tilde{P}_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} + (\ln \tilde{P}_i - \ln C_i) + v_i \quad (8)$$

The first-order Taylor series expansion of $\ln(\tilde{P}_i/C_i)$ at $\frac{\tilde{P}_i}{C_i} = 1$ is:

$$\ln(\tilde{P}_i/C_i) \approx \ln(1) + \left. \frac{\partial \ln(\tilde{P}_i/C_i)}{\partial (\tilde{P}_i/C_i)} \right|_{\tilde{P}_i/C_i=1} \cdot \left(\frac{\tilde{P}_i}{C_i} - 1 \right) = \frac{\tilde{P}_i}{C_i} - 1 \quad (9)$$

By incorporating the optimality condition (6), the expression of (9), and $\beta_k = \frac{\partial \ln C_i}{\partial z_{ik}}$, the hedonic regression model in (8) can be rewritten as follows.

$$\begin{aligned} \ln \tilde{P}_i = \beta_0 + \sum_{k=1}^K \frac{1}{C_i} \frac{\partial \tilde{\pi}_i}{\partial z_{ik}} \frac{1 - T_i^s}{1 + T_i^b} \left(1 - \left(1 - \frac{1 + T_i^b}{1 - T_i^s} \frac{C_i}{\tilde{P}_i} \right) \frac{1}{\sigma_{ik}} \right) z_{ik} + \left(\frac{\tilde{P}_i}{C_i} - 1 \right) \\ + v_i \end{aligned} \quad (10)$$

Let $1 - \hat{T}_i = \frac{1 - T_i^s}{1 + T_i^b}$. Then Equation (10) can be modified as follows.

$$\begin{aligned} \ln \tilde{P}_i = \beta_0 + \sum_{k=1}^K \frac{1 - \hat{T}_i}{C_i(\mathbf{z}_i^*)} \frac{\partial \tilde{\pi}_i}{\partial z_{ik}} \left(1 - \left(1 - \frac{C_i(\mathbf{z}_i^*)}{(1 - \hat{T}_i) \tilde{P}_i} \right) \frac{1}{\sigma_{ik}} \right) z_{ik} + \left(\frac{\tilde{P}_i}{C_i} - 1 \right) \\ + v_i \end{aligned} \quad (11)$$

Recall $\tilde{P}_i = \tilde{\pi}_i(q_i, \mathbf{z}_i)$. Define $\gamma_{ik} = \frac{\partial \ln \tilde{\pi}_i}{\partial z_{ik}} \frac{1}{\tilde{\pi}_i} = \frac{\partial \tilde{\pi}_i}{\partial z_{ik}} \frac{1}{\tilde{P}_i}$ as the marginal value of z_{ik}

on $\ln \tilde{P}_i$. Equation (11) becomes:

$$\begin{aligned} \ln \tilde{P}_i = & \beta_0 + \sum_{k=1}^K \frac{\tilde{P}_i}{C_i} \gamma_{ik} z_{ik} (1 - \hat{T}_i) + \sum_{k=1}^K \frac{\tilde{P}_i}{C_i} \frac{\gamma_{ik} z_{ik}}{\sigma_{ik}} \hat{T}_i \\ & + \left(\frac{\tilde{P}_i}{C_i} - 1 \right) \left(1 - \sum_{k=1}^K \frac{\gamma_{ik} z_{ik}}{\sigma_{ik}} \right) + v_i \end{aligned} \quad (12)$$

Similar to Feenstra (p.653, 1995), we assume $\tilde{\pi}_i(q_i, \mathbf{z}_i)$ takes the general form,

$f_i(q_i, \mathbf{z}_i) + g_i(\mathbf{z}_i)$, where $f_i(q_i, \mathbf{z}_i)$ is homogeneous of degree one in \mathbf{z}_i . Then, Then, given that

$$\sum_k \frac{\gamma_{ik} z_{ik}}{\sigma_{ik}} = \sum_k \frac{\frac{1}{\tilde{\pi}_i} \frac{\partial \tilde{\pi}_i}{\partial z_{ik}} z_{ik}}{\frac{\partial \tilde{\pi}_i}{\partial z_{ik}} \frac{\partial \tilde{\pi}_i}{\partial q_i} \left(\tilde{\pi}_i \frac{\partial^2 \tilde{\pi}_i}{\partial q_i \partial z_{ik}} \right)^{-1}} = \sum_k \frac{\frac{\partial^2 \tilde{\pi}_i}{\partial q_i \partial z_{ik}} z_{ik}}{\frac{\partial \tilde{\pi}_i}{\partial q_i}}, \text{ it is straightforward to show } 1 - \sum_k \frac{\gamma_{ik} z_{ik}}{\sigma_{ik}} = 0.$$

Applying this result, the hedonic price model in (12) can be simplified as follows.

$$\ln \tilde{P}_i = \beta_0 + \sum_k \frac{\tilde{P}_i}{C_i} \gamma_{ik} z_{ik} (1 - \hat{T}_i) + \frac{\tilde{P}_i}{C_i} \hat{T}_i + v_i \quad (13)$$

As seen in Equation (13) the natural log of the final price paid by consumers can be presented as a linear function of the characteristics of the goods, a composite tax variable, and the product of the characteristics and the tax variable. Note that the price-cost ratio appears in all terms except for the intercept, similar to the result in Feenstra (1995). A key new result here is that the coefficient of the composite tax variable is the price-cost ratio. Once the coefficient of the tax variable is estimated, it can be used to recover estimates of γ_{ik} from the estimated coefficients of the above price equation.

The above analysis is based on the assumption of a semi-log cost function and it arrives at the semi-log functional form that is most commonly used in empirical hedonic price analysis. Alternatively, if the cost function is linear:

$$C_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} + v_i \quad (14)$$

By adding $\tilde{P}_i - C_i$ and substituting β_k with $\frac{\partial C_i}{\partial z_{ik}}$ on both sides of (14), the hedonic price model can be written as follows.

$$\tilde{P}_i = \beta_0 + \sum_{k=1}^K \frac{\partial \tilde{\pi}_i}{\partial z_{ik}} \frac{1 - T_i^s}{1 + T_i^b} \left(1 - \left(1 - \frac{1 + T_i^b}{1 - T_i^s} \frac{C_i}{\tilde{P}_i} \right) \frac{1}{\sigma_{ik}} \right) z_{ik} + (\tilde{P}_i - C_i) + v_i \quad (15)$$

Define $\hat{\gamma}_{ik} = \frac{\partial \tilde{\pi}_i(q_i^*, z_i^*)}{\partial z_{ik}}$ as the marginal value of z_{ik} . Equation (15) can be re-arranged as follows.

$$\begin{aligned} \tilde{P}_i = \beta_0 + \sum_{k=1}^K \hat{\gamma}_{ik} z_{ik} \frac{1 - T_i^s}{1 + T_i^b} + \frac{T_i^b + T_i^s}{1 + T_i^b} \tilde{P}_i \sum_{k=1}^K \frac{\hat{\gamma}_{ik} z_{ik}}{\tilde{P}_i \sigma_{ik}} \\ + (\tilde{P}_i - C_i) \left(1 - \sum_{k=1}^K \frac{\hat{\gamma}_{ik} z_{ik}}{\tilde{P}_i \sigma_{ik}} \right) + v_i \end{aligned} \quad (16)$$

Based on the same assumption on $\tilde{\pi}_i(q_i, z_i)$, it is easy to show that $\sum_k \frac{\hat{\gamma}_{ik} z_{ik}}{\tilde{P}_i \sigma_{ik}} = \sum_k \frac{\gamma_{ik} z_{ik}}{\sigma_{ik}} =$

1. Then, Equation (16) can be simplified and re-arranged as follows.

$$\begin{aligned} \tilde{P}_i = \beta_0 + \sum_{k=1}^K \hat{\gamma}_{ik} z_{ik} \frac{1 - T_i^s}{1 + T_i^b} + \frac{T_i^b + T_i^s}{1 + T_i^b} \tilde{P}_i + v_i \\ \Rightarrow (1 - T_i^s) P_i = \beta_0 + \sum_{k=1}^K \hat{\gamma}_{ik} z_{ik} (1 - \hat{T}_i) + v_i \end{aligned} \quad (17)$$

where $(1 - T_i^s) P_i$ is the after-tax price received by the firm. Empirically we may regress $(1 - T_i^s) P_i$ linearly on $z_{ik}(1 - \hat{T}_i)$ to derive the marginal values of product characteristics, $\hat{\gamma}_{ik}$. Note that if empirically we run the standard linear hedonic price regression without the variable transformation as presented in Equation (17) that accounts for potential market power, the resulting estimated marginal values do not necessarily reflect the influence of market power.

3. Monte Carlo Simulation

We simulate our data from a general equilibrium model under imperfect competition. The purpose is to compare the traditional approach, which ignores imperfect competition, with our proposed approach, which explicitly takes into account both taxation and imperfect competition. As in Section 2, we consider both the tax imposed on consumers (T^b) and the tax imposed on producers (T^s).

3.1 Design of the True Model

The true model is a modified version of Feenstra's (1995) CES model.² Assume there are M individuals. Each individual consumes a variable number of units x_i of product i and spends the rest of income (Y) on the numeraire good, x_0 . The individual utility of choosing product i is specified as follows.

$$U_i = \alpha \ln(x_0 - \phi x_i) + \ln(x_i z_i) + e_i, \quad i = 1, \dots, N \quad (18)$$

where e_i is the unobservable component of the utility function. For each i , individuals maximize (18) subject to the budget constraint, $x_0 + \tilde{P}_i x_i = Y$. The corresponding indirect utility function can be derived as follows.

$$V_i = (1 + \alpha) \ln(y) - \ln\left(\frac{\tilde{P}_i + \phi}{z_i}\right) + b + e_i \quad (19)$$

$$\text{where } b = \alpha \ln(\alpha) - (1 + \alpha) \ln(1 + \alpha)$$

According to Feenstra (1995), a quality adjusted price of product i (q_i) can be defined as $\frac{\tilde{P}_i + \phi}{z_i}$. By inverting the quality adjusted price function, we obtain $\tilde{P}_i = \tilde{\pi}_i(q_i, z_i) = q_i z_i - \phi$.

Then, the marginal value of characteristic z_i is:

$$\gamma_i = \frac{\partial \ln \tilde{\pi}_i}{\partial z_i} = \frac{q_i}{q_i z_i - \phi} \quad (20)$$

² Feenstra's (1995) CES model does not allow z to appear in Equation (13), because $\gamma \cdot z = 1$. To allow his CES model to be operational, we modify his utility function by subtracting ϕx_i from x_0 in (18).

Next, we assume that ε_i follows the double exponential distribution:

$$F_i(\varepsilon_i) = \exp\left\{-\exp\left[-\left(\frac{e_i}{\mu} + v\right)\right]\right\}, \quad (21)$$

where v is Euler's constant. Based on the distributional assumption of e_i , we derive the following expected Marshallian demand.

$$X_i(\tilde{P}_i, z_i; \tilde{P}_{-i}, z_{-i}) = M \frac{y}{(\tilde{P}_i + \varphi)(1 + \alpha)} \left\{ \frac{\left(\frac{\tilde{P}_i + \varphi}{z_i}\right)^{-1/\mu}}{\sum_{j=1}^N \left(\frac{\tilde{P}_j + \varphi}{z_j}\right)^{-1/\mu}} \right\} \quad (22)$$

For the supply side, we assume each differentiated product i is produced by only one firm. Then, similar to the setup in Section 2, the profit maximization of a firm selling product i is described as follows.

$$\max_{\tilde{P}_i, z_i} \left[\tilde{P}_i \frac{1 - T_i^s}{1 + T_i^b} - C_i(z_i) \right] X_i(\tilde{P}_i, z_i; \tilde{P}_{-i}, z_{-i}), \quad i = 1, \dots, N \quad (23)$$

The first order conditions for the firm's maximization problem are:

$$\frac{C_i(z_i)}{\tilde{P}_i} = \frac{1 - T_i^s}{1 + T_i^b} \frac{1 + \varepsilon_i(\tilde{P}, z)}{\varepsilon_i(\tilde{P}, z)} \quad (24)$$

$$\frac{\partial C_i(z_i)}{\partial z_i} = \left[\frac{1 - T_i^s}{1 + T_i^b} \frac{\tilde{P}_i}{z_i} - \frac{C_i(z_i)}{z_i} \right] \eta_i(\tilde{P}, z) \quad (25)$$

where $\varepsilon_i(\tilde{P}, z) = \frac{\partial X_i(\tilde{P}, z; \tilde{P}_{-i}, z_{-i})}{\partial \tilde{P}_i} \frac{\tilde{P}_i}{X_i(\tilde{P}, z; \tilde{P}_{-i}, z_{-i})}$ and $\eta_i(\tilde{P}, z) = \frac{\partial X_i(\tilde{P}, z; \tilde{P}_{-i}, z_{-i})}{\partial z_i} \frac{z_i}{X_i(\tilde{P}, z; \tilde{P}_{-i}, z_{-i})}$.

The last assumption of the model is about the functional form of $C_i(z_i)$. As seen in the previous section, different assumptions of C_i lead to different empirical specifications of the hedonic price function. With a semi-log cost function, the price-cost ratio is embedded in the coefficients in the resulting semi-log price equation. To investigate this important issue, we assume a semi-log cost function:

$$\ln C_i(z_i) = \beta_0 + \beta_1 z_i \quad (26)$$

Then, Equations (24) and (25) can be simplified and rearranged as follows.

$$z_i = \frac{-\eta_i(\tilde{P}, z)}{\beta_1 (1 + \varepsilon_i(\tilde{P}, z))} \quad (27)$$

$$\tilde{P}_i = \frac{1 + T_i^b}{1 - T_i^s} \frac{\varepsilon_i(\tilde{P}, z)}{1 + \varepsilon_i(\tilde{P}, z)} e^{\beta_0 + \beta_1 z_i} \quad (28)$$

Both (27) and (28) determine the optimal choices of prices and characteristics, which ultimately depend on the values of 5 model parameters ($N, \beta_0, \beta_1, \mu, \varphi$) and the tax rates (T_i^s, T_i^b).

In this experiment, we simulate our data from eight different sets of true models. Four of them consider the tax imposed on consumers ($T_i^b > 0, T_i^s = 0$), and the other four consider the tax imposed on producers ($T_i^s > 0, T_i^b = 0$). For each true model, we generate 500 different datasets, with a sample size of 200 for each dataset. Table 1 summarizes the parameter values used in the simulation.

3.2 Evaluation Criterion

We use the normalized root mean squared error (*NRMSE*) as the criterion for evaluating the quality of estimates of the marginal value of characteristics.

$$NRMSE = \sqrt{\frac{1}{K} \sum_{n=1}^K \left(\frac{estValue_k - trueValue_k}{trueValue_k} \right)^2}, \quad (29)$$

where K is the total number of datasets, *trueValue* is the true marginal value of characteristics, and *estValue* is the estimated marginal value of characteristics.

3.3 Empirical Models

For each dataset, we estimate five different empirical models.³

$$\text{M1: } \ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \epsilon_i$$

$$\text{M2: } \ln \check{P}_i = \alpha_0 + \alpha_1 z_i + \epsilon_i$$

$$\text{M3: } \ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \alpha_2 T_i + \epsilon_i$$

$$\text{M4: } \ln \check{P}_i = \alpha_0 + \alpha_1 z_i + \alpha_2 T_i + \epsilon_i$$

$$\text{M5: } \ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i (1 - \hat{T}_i) + \alpha_2 \hat{T}_i + \epsilon_i$$

where \tilde{P}_i and \check{P}_i are the after-tax prices received by consumers and producers respectively. The marginal value of characteristics in M5 is α_1/α_2 , while in the other empirical models the marginal value is measured by α_1 . As explained in Section 2, only M5 takes into account imperfect competition and the impacts of taxation, which are consistent with the theoretical model.

3.4 Simulation Results

The simulation results are summarized in Table 2. As seen in Table 2, the empirical model M5 outperforms the other empirical models by producing the smallest *NRMSE*. In addition, the average marginal values of characteristics computed from M5 are consistently close to the true values across different data generation processes.

It is important to note that the simulation results from Table 2 do not necessarily imply M5 is the best empirical model. Rather, it represents a convenient estimation strategy that works. First, M5 treats α_1 and α_2 as constant coefficients, which are not consistent with the theoretical model. Second, those α terms correlate with z and the tax variable, leading to an endogeneity problem. In other words, the OLS estimates of α_1 and α_2 will be biased. However, our

³ Since the underlying true price function is in a semi-log form, we omit linear equations and focus on the comparison of different specifications of semi-log price equations in the simulation study.

simulation results show that the ratio of two biased estimates cancel out some of biases.

Comparing to M5, models M1-M4 have no theoretical underpinning to suggest any counter measure for the potential bias in the coefficient estimates. Though it is important to continue to search for a better estimation procedure to estimate M5, the bottom line from our simulation results shows that the traditional approach, which ignores or does not address appropriately the role of taxation and/or imperfect competition, can be problematic.

4. Case Study – Consumer Values for Ski Resort Amenities

The U.S. ski industry is a multi-billion dollar industry. There are a good variety of ski areas across the country with varying amenities to provide potentially unique ski experience. We study the 2011-12 ski season and compile a data set that contains the price of a lift ticket and characteristics of ski areas in the U.S. In our data set, 322 ski areas have necessary information for our analysis, representing over 75 percent of all operational ski areas during the studied season. Table 4 provides summaries of the ski areas by region in our data set. The ski areas in our analysis cover various geographical regions (Northeast, South, Mid-west, West). The data include all types of ski areas from small rope tow only areas to mountains with over 100 trails and nearly 5000 foot vertical drops.

Table 5 gives the definition and summary statistics of all variables, including attributes and characteristics of a ski area (e.g., number of trails, difficulty of trails, the vertical drop of the mountain, skiable area, number of ski lifts), and location variables. Note that some ski areas charge different prices during different times of the day or season. Since all ski area in the data set were open on the weekend and sold an 8 hour pass each weekend day during the study

period, we focus our analysis on the full-day weekend lift ticket price.⁴ It has been widely hypothesized, among the industry experts, that skiers prefer natural snow over artificial snow. Hence, we also include two weather related variables, annual snowfall in the region and percent of total skiable area that can be covered with artificial snow. Two taxes, sales tax and tourism tax, are included in the data analysis. Both taxes are imposed on consumers. In the ski industry, sales tax and tourism tax can be added on top of the list price of a lift ticket or included in the list price. Hence, the list price of a lift ticket needs to be adjusted according to the tax collection practice of the ski areas.

Various specifications of the hedonic price models are considered. Table 5 presents estimation results of linear models. Models 1 and 2 are the typical hedonic price equations to regress price on relevant explanatory variables. The difference between Models 1 and 2 is the inclusion of regional dummy variables in Model 2. Models 3 and 4 utilize Equation (17) to guide the construction of the price variable (dependent variable) and independent variables so that the empirical model specification is consistent with our theoretical results. According to Equation (17), the composite tax variable does not enter the price equation independently. Rather, it is multiplied to other explanatory variables. Model 4 also includes regional dummy variables.

The estimation results show that in general characteristics of ski areas affect pricing of lift tickets and larger ski areas command a higher price for lift tickets (as indicated by the positive and significant coefficients of Trails and Lifts). Natural snow adds value and all else equal snowmaking facilities are desired. The tax variables are insignificant in the standard hedonic price models (Models 1 and 2).

⁴ Other options for the dependent variable would be half-day passes or weekday passes as well as peak period passes, however, not all ski areas have these different prices.

Table 6 reports the estimation results of the semi-log hedonic price models. Models 5 and 6 are the standard models; Models 7 and 8 are specified according to the theoretical results presented in Equation (13) that the composite tax variable enters the price equation directly by itself and indirectly with other explanatory variables. Importantly, the coefficient of the composite tax variable is the price-cost ratio as seen in Equation (13). The qualitative results of the semi-log models are similar to those of the linear models. Size of ski areas and snowfall matter to the pricing of ski lift tickets. The composite tax variable is significant in the theoretically consistent Models 7 and 8. Its coefficient, the price-cost ratio, is estimated at around 1.5. The estimate of price-cost ratio will enable the recovery of marginal values of characteristics of ski areas from the rest of the coefficient estimates.

Before comparing the estimated marginal values from different empirical models, it is important to examine the goodness of fit of the different empirical models. The two key empirical models to compare are the semi-log and linear models supported by the theoretical results in Section 2.

$$A1: \ln \tilde{P}_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} (1 - \hat{T}_i) + \eta \hat{T}_i + R_i + \epsilon_i \quad (30)$$

$$A2: P_i = \alpha_0 + \sum_{k=1}^K \alpha_k z_{ik} (1 - \hat{T}_i) + R_i + \epsilon_i \quad (31)$$

where R_i is a regional dummy variable. Among the eight estimated models, Model 4 mimics A2 and Model 8 mimics A1. Note that there is no simple goodness of fit measure to compare A1 with A2 directly because the two models have different variables on both LHS and RHS. We develop a 3-step model selection procedure to choose between A1 and A2. In Step 1, we estimate the following box-cox model:

$$\tilde{P}_i^\theta = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} (1 - \hat{T}_i) + \eta \hat{T}_i + R_i + \epsilon_i,$$

$$\text{where } \tilde{P}_i^\theta = \begin{cases} \tilde{P}_i - 1 & \text{if } \theta = 1 \\ \ln(\tilde{P}_i) & \text{if } \theta = 0 \\ 1 - 1/\tilde{P}_i & \text{if } \theta = -1 \end{cases}$$

According to the box-cox test results reported in Table 7, the following linear model (A3) is preferred over A1.

$$\text{A3: } \tilde{P}_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} (1 - \hat{T}_i) + \eta \hat{T}_i + R_i + \epsilon_i \quad (32)$$

In Step 2, we employ a cross-validation procedure and use prediction errors to choose between A2 and A3. First, we use $N-1$ observations to estimate A2 and A3, and then use the estimated models to predict \tilde{P}_i for the observation that has been dropped. For A3, the predicted value is \hat{P}_i , so it should be multiplied with $1 + T_i$, where T_i is the sum of sales and tourism taxes, to recover \tilde{P}_i . Second, we repeat the first step for every observation in the data sample, and then compute the mean square error (MSE). According to the MSEs reported in Table 7, A2 is preferred over A3. In other words, the linear model A2 is preferred over the semi-log model A1.

To ensure that the theoretically supported linear model A2 is the linear model supported by the data, in Step 3, we compare A2 with a standard linear specification, A4.

$$\text{A4: } P_i = \alpha_0 + \sum_{k=1}^K \alpha_k z_{ik} + \eta T_i + R_i + \epsilon_i \quad (33)$$

Given that both A2 and A4 share the same dependent variable, we use AIC and BIC as model selection criteria. As reported in Table 7, both AIC and BIC choose A2 over A4. The results of our model selection procedure suggest that Model 4 is the best model choice for the ski data.

For a standard linear hedonic price equation, the coefficients are the marginal values. When the market power is taken into account, as seen in Equation (17), once the dependent and independent variables are properly transformed in the hedonic price equation, the estimated coefficients are also the estimated marginal values. The numbers in the first two columns of Table 8 are the estimated marginal values based on Models 2 and 4, respectively. As seen, the estimated marginal values of characteristics of ski areas are quite different between the two models. Without taking into account imperfect competition that leads to the potential price-cost markup, marginal values of ski area characteristics can be over- or under-estimated. Hence, Feenstra (1995)'s theoretical finding that the coefficients of the standard linear hedonic price model can still reflect the marginal values of product characteristics under imperfect competition is correct only if proper variable transformations, as shown in Equation (17), are applied.

For comparison, the estimated marginal values based on the standard semi-log Model 6 and the theoretically consistent Model 8 are also presented in Table 8. In order to be comparable to the linear models, the marginal values computed from the semi-log models are adjusted based on $\partial \tilde{\pi}_i / \partial z_{ik}$. In other words, the estimated marginal values from Model 6 are computed as the estimated coefficients multiplied by the average price. The estimated marginal values from Model 8 are recovered by dividing all the estimated coefficients by the estimated coefficient of the composite tax variable, and then multiplied by the average price. It appears that the estimated marginal values of characteristics of ski areas are generally higher when price-cost markup due to imperfect competition is ignored, as shown by Feenstra (1995).

5. Remarks

Empirical hedonic price studies for environmental valuation often overlook the potential effects of market power on pricing. In this study, we derive the theoretically consistent specification of hedonic price equations under imperfect competition when firms' cost function is in linear or semi-log form. We show the variable transformations and specific model specification necessary for theoretically consistent estimation of hedonic price equations under imperfect competition.

The role of taxation is closely examined in our analysis partly because taxes affect the total cost of consumption and can be capitalized into product prices. Importantly, we show that methodologically taxes provide a means to identify the size of price-cost markup to help recover marginal values of product characteristics in the hedonic method for non-market valuation. This study enables the realistic and appropriate use of hedonic method for non-market valuation under imperfect competition.

In the case study, we assume constant price-cost markup to simplify the estimation. Realistically price-cost ratio can vary across firms. Further, it can correlate with product characteristics and the tax variable. Future research to incorporate varying coefficients and to address potential endogeneity issue in estimation is warranted.

References

- Chattopadhyay, Sudip. "Estimating the Demand for Air Quality: New Evidence Based on the Chicago Housing Market." *Land Economics*. Vol. 75. No. 1. 1999. pp 22-38.
- Bajari, Patrick and C. Lanier Benkard. 2005. "Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach." *Journal of Political Economy*. Vol. 113. No. 6. 2005. pp 1239-76.
- Caplin, Andrew, and Barry Nalebuff. "Aggregation and Imperfect Competition: On the Existence of Equilibrium." *Econometrica*. Vol. 59. No. 1. 1991. pp 26-61.
- Chay, Kenneth Y. and Michael Greenstone. "Does Air Quality Matter? Evidence from the Housing Market." *Journal of Political Economy*. Vol. 113. No. 2. 2005. pp 376-424.
- Feenstra, Robert C. "Exact Hedonic Price Indexes." *The Review of Economics and Statistics*. Vol. 77. 1995. pp 634-653.
- Gyourko Joseph and Joseph Tracy. "The Structure of Local Public Finance and the Quality of Life." *Journal of Political Economy*. Vol. 99, No. 4. 1991. pp 774-806.
- McFadden, Daniel. "Modeling the Choice of Residential Location." in A. Krlqvist, L. Lundqvist, F. Snickars, and J. Weibull (eds.), *Spatial Interaction Theory and Planning Models*. 1978. pp 75-96. Amsterdam: North-Holland.
- Milgrom, Paul, and John Roberts. "Rationalizability, Learning, and Equilibrium in Games with Strategic Complementarities." *Econometrica*. Vol.58, No. 6. 1990. pp 1255-1277.
- Oktem, Mustafa; and Ju-Chin Huang. "Property Tax Shifting under Imperfect Competition." *Applied Economics*. Vol. 43. 2011. pp 139-152.
- Rosen, Sherwin. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy*. Vol. 82. Issue 1. 1974. pp 34-55.
- Smith, V. Kerry, and Ju-Chin Huang. "Can Markets Value Air Quality? A Meta-analysis of Hedonic Property Value Models." *Journal of Political Economy*. Vol. 103. No. 1. 1995. pp 209-227.
- Taylor, Laura O. and V. Kerry Smith. "Environmental Amenities as a Source of Market Power." *Land Economics*. Vol. 76. No. 4. 2000. pp 550-568.

Table 1. Parameter Values in Simulation

	Fixed in each dataset	Vary across datasets
S1	$N = 200, \beta_1 = 1, \mu = 1, \varphi = 1, T_i^S = 0$	$\beta_0 \sim \text{uniform}(1,3)$
S2	$N = 200, \beta_0 = 1, \mu = 1, \varphi = 1, T_i^S = 0$	$\beta_1 \sim \text{uniform}(1,3)$
S3	$N = 200, \beta_0 = 1, \beta_1 = 1, \varphi = 1, T_i^S = 0$	$\mu \sim \text{uniform}(1,3)$
S4	$N = 200, \beta_0 = 1, \beta_1 = 1, \mu = 1, T_i^S = 0$	$\varphi \sim \text{uniform}(1,3)$
S5	$N = 200, \beta_1 = 1, \mu = 1, \varphi = 1, T_i^b = 0$	$\beta_0 \sim \text{uniform}(1,3)$
S6	$N = 200, \beta_0 = 1, \mu = 1, \varphi = 1, T_i^b = 0$	$\beta_1 \sim \text{uniform}(1,3)$
S7	$N = 200, \beta_0 = 1, \beta_1 = 1, \varphi = 1, T_i^b = 0$	$\mu \sim \text{uniform}(1,3)$
S8	$N = 200, \beta_0 = 1, \beta_1 = 1, \mu = 1, T_i^b = 0$	$\varphi \sim \text{uniform}(1,3)$

Notes:

- (1) S1-S4: $T_i^b \sim \text{uniform}(0,10\%)$, varies across firms and datasets.
(2) S5-S6: $T_i^S \sim \text{uniform}(0,10\%)$, varies across firms and datasets.

Table 2. Simulation Results

	Mean Values					
	M1	M2	M3	M4	M5	Truth
S1	-25.698 (30.550)	1.554 (0.596)	-4.507 (5.695)	0.728 (0.426)	0.782 (0.199)	0.974
S2	-16.589 (9.691)	3.029 (0.587)	-7.733 (5.039)	2.955 (0.546)	1.462 (0.234)	1.909
S3	-8.068 (9.691)	1.626 (0.756)	-3.127 (4.370)	1.328 (0.437)	0.708 (0.237)	0.928
S4	-4.645 (6.275)	1.468 (0.628)	-1.942 (3.185)	1.321 (0.472)	0.614 (0.322)	0.902
S5	-25.816 (30.670)	1.555 (0.595)	-1.151 (2.661)	0.018 (0.982)	0.802 (0.180)	0.975
S6	-16.657 (9.704)	3.029 (0.583)	-59.583 (33.989)	1.976 (0.327)	1.465 (0.235)	1.914
S7	-8.101 (9.711)	1.626 (0.753)	-3.701 (5.060)	0.145 (0.845)	0.714 (0.232)	0.930
S8	-4.664 (6.276)	1.468 (0.621)	-5.813 (7.517)	0.584 (0.461)	0.618 (0.321)	0.906

Notes:

(1) The numbers in the brackets are *NRMSE*.

(2) M1: $\ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \epsilon_i$

(3) M2: $\ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \epsilon_i$

(4) M3: $\ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \alpha_2 T_i + \epsilon_i$

(5) M4: $\ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i + \alpha_2 T_i + \epsilon_i$

(6) M5: $\ln \tilde{P}_i = \alpha_0 + \alpha_1 z_i (1 - \hat{T}_i) + \alpha_2 \hat{T}_i + \epsilon_i$

(7) \tilde{P}_i and \tilde{P}_i are the after-tax prices received by consumers and firms, respectively.

Table 3. Characteristic Averages of Ski Areas in Data Set (2011-2012)

	Number of Ski Areas	Average Number of Trails	Average Vertical Drop (feet)
Northeast	100 (126)	39.9	1137
South	16 (17)	19.1	754
Mid-West	79 (116)	22.8	374
West	127 (168)	58.4	1869
Total	322 (427)	42.0	1219

Note: The numbers in the brackets are the total number of ski areas in each region.

Table 4. Summary Statistics

Variable	Definition	Mean	S.D.	Min	Max
Lift Ticket Price	Price of the full-day weekend lift ticket (after tax)	53.57	18.57	11	105
Trails	Number of skiable trails	42.00	35.65	2	193
Vertical	Vertical drop of the mountain measured in 100 feet.	12.19	9.64	0.4	44.25
Elevation	Base elevation of the ski area measured in 100 feet.	33.05	31.16	0	107.8
Lifts	Number of operational non-rope-tow lifts at the mountain.	6.09	4.77	0	33
Area	Skiable area of the mountain measured in 100 acres.	5.94	9.36	0.08	70
Beginner	Percentage of trails designated as beginner level difficulty.	26.73	10.70	0	80
Moderate	Percentage of trails designated as moderate level difficulty.	40.88	11.02	1	70
Advanced	Percentage of trails designated as advanced level difficulty.	32.32	12.75	0	99
Snowfall	Average annual snowfall measured in 100 inches.	1.81	1.40	0	7.82
Snowmaking	Percentage of the skiable area that can be covered with artificial snow using snowmaking equipment.	62.95	41.39	0	100
Sales Tax	State sales tax.	0.049	0.021	0	0.075
Tourism Tax	State tourism tax.	0.049	0.024	0	0.12

Table 5. Linear Models

Model:	(1)	(2)	Model:	(3)	(4)
Dep. Variable:	Before-Tax Ticket Price		Dep. Variable:	Before-Tax Ticket Price	
Advanced	-0.0224 (0.0640)	0.0180 (0.0656)	Advanced·(1- \hat{T} ax)	-0.0385 (0.0761)	0.00445 (0.0779)
Moderate	0.0390 (0.0575)	0.0877 (0.0593)	Moderate·(1- \hat{T} ax)	0.0371 (0.0615)	0.0904 (0.0650)
Elevation	0.0754** (0.0337)	0.102*** (0.0348)	Elevation·(1- \hat{T} ax)	0.0788** (0.0339)	0.105*** (0.0369)
Trails	0.0976** (0.0395)	0.104** (0.0427)	Trails·(1- \hat{T} ax)	0.109*** (0.0398)	0.116** (0.0446)
Lifts	1.032*** (0.236)	1.027*** (0.240)	Lifts·(1- \hat{T} ax)	1.146*** (0.252)	1.138*** (0.259)
Vertical	0.755*** (0.123)	0.588*** (0.124)	Vertical·(1- \hat{T} ax)	0.810*** (0.130)	0.628*** (0.126)
Area	-0.0247 (0.106)	0.0579 (0.108)	Area·(1- \hat{T} ax)	-0.0503 (0.113)	0.0380 (0.112)
Snowfall	0.763 (0.915)	1.054 (0.885)	Snowfall·(1- \hat{T} ax)	0.908 (0.957)	1.212 (0.932)
Snowmaking	0.135*** (0.0292)	0.110*** (0.0259)	Snowmaking·(1- \hat{T} ax)	0.148*** (0.0319)	0.120*** (0.0279)
Tax	-20.36 (25.52)	-21.42 (21.97)			
Northeast		5.738** (2.339)			5.871** (2.311)
South		11.11** (4.089)			11.27*** (4.055)
West		-0.462 (2.733)			-0.155 (2.847)
Constant	18.19*** (4.808)	14.37*** (4.477)		16.98*** (3.169)	12.95*** (3.648)
N	322	322	N	322	322
R-squared	0.701	0.727	R-squared	0.701	0.727

Notes:

(1) Standard errors are clustered at the state level.

(2) Tax = Sales Tax+ Tourism Tax

(3) \hat{T} ax = $1 - 1/(1 + \text{Tax})$.

(4) *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Semi-Log Models

Model:	(5)	(6)	Model:	(7)	(8)
Dep. Variable:	Ln(Before-Tax Ticket Price)		Dep. Variable:	Ln(After-Tax Ticket Price)	
Advanced	0.000748 (0.00179)	0.00176 (0.00189)	Advanced·(1- $\hat{\text{Tax}}$)	0.000594 (0.00191)	0.00171 (0.00205)
Moderate	0.00154 (0.00166)	0.00276 (0.00174)	Moderate·(1- $\hat{\text{Tax}}$)	0.00162 (0.00182)	0.00298 (0.00191)
Elevation	0.00200** (0.000801)	0.00245*** (0.000832)	Elevation·(1- $\hat{\text{Tax}}$)	0.00213** (0.000864)	0.00253*** (0.000906)
Trails	0.00137* (0.000772)	0.00160* (0.000802)	Trails·(1- $\hat{\text{Tax}}$)	0.00153* (0.000816)	0.00181** (0.000846)
Lifts	0.0205*** (0.00504)	0.0201*** (0.00475)	Lifts·(1- $\hat{\text{Tax}}$)	0.0227*** (0.00552)	0.0223*** (0.00519)
Vertical	0.0169*** (0.00237)	0.0127*** (0.00254)	Vertical·(1- $\hat{\text{Tax}}$)	0.0182*** (0.00250)	0.0136*** (0.00262)
Area	-0.00139 (0.00301)	0.000490 (0.00294)	Area·(1- $\hat{\text{Tax}}$)	-0.00203 (0.00326)	-4.64e-05 (0.00312)
Snowfall	0.0350* (0.0174)	0.0411** (0.0157)	Snowfall·(1- $\hat{\text{Tax}}$)	0.0398** (0.0186)	0.0461*** (0.0167)
Snowmaking	0.00390*** (0.000774)	0.00335*** (0.000789)	Snowmaking·(1- $\hat{\text{Tax}}$)	0.00422*** (0.000833)	0.00364*** (0.000857)
Tax	-0.338 (0.574)	-0.340 (0.515)	$\hat{\text{Tax}}$	1.481** (0.725)	1.554** (0.671)
Northeast		0.141** (0.0576)	Northeast		0.145** (0.0575)
South		0.275*** (0.0888)	South		0.281*** (0.0888)
West		0.0120 (0.0613)	West		0.0233 (0.0586)
Constant	3.013*** (0.136)	2.909*** (0.134)	Constant	2.958*** (0.146)	2.841*** (0.147)
N	322	322	N	322	322
R-squared	0.614	0.644	R-Squared	0.605	0.636

Notes:

(1) Standard errors are clustered at the state level.

(2) Tax = Sales Tax+ Tourism Tax

(2) $\hat{\text{Tax}} = 1 - 1/(1 + \text{Tax})$.

(3) *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Model Selection

Step 1: Box-Cox Results			
$\tilde{P}_i^\theta = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} (1 - \hat{T}_i) + \eta \hat{T}_i + R_i + \varepsilon_i$			
	Restricted log		
	likelihood	LR statistic	P-value
$\theta = -1$	-1401.14	416.11	0.000
$\theta = 0$	-1242.20	98.24	0.000
$\theta = 1$	-1193.10	0.04	0.845
Step 2: Prediction Errors			
A2: $P_i = \alpha_0 + \sum_{k=1}^K \alpha_k z_{ik} (1 - \hat{T}_i) + R_i + \varepsilon_i$			
A3: $\tilde{P}_i = \beta_0 + \sum_{k=1}^K \beta_k z_{ik} (1 - \hat{T}_i) + \eta \hat{T}_i + R_i + \varepsilon_i$			
	A2		A3
MSE	107.35		107.65
Step 3: AIC and BIC			
A2: $P_i = \alpha_0 + \sum_{k=1}^K \alpha_k z_{ik} (1 - \hat{T}_i) + R_i + \varepsilon_i$			
A4: $P_i = \alpha_0 + \sum_{k=1}^K \alpha_k z_{ik} + \eta T_i + R_i + \varepsilon_i$			
	A2		A4
AIC	2355.31		2357.90
BIC	2404.38		2410.75

Table 8. Marginal Values of the Characteristics ($\partial\tilde{\pi}_i/\partial z_{ik}$)

Empirical Model	Linear Model		Semi-Log Model	
	Ignore Imperfect Competition (2)	Consider Imperfect Competition (4)	Ignore Imperfect Competition (6)	Consider Imperfect Competition (8)
Advanced	0.0180 (0.0656)	0.00445 (0.0779)	0.094 (0.101)	0.059 (0.071)
Moderate	0.0877 (0.0593)	0.0904 (0.0650)	0.148 (0.093)	0.103 (0.065)
Elevation	0.102*** (0.0348)	0.105*** (0.0369)	0.131*** (0.045)	0.087** (0.041)
Trails	0.104** (0.0427)	0.116** (0.0446)	0.086* (0.043)	0.062 (0.045)
Lifts	1.027*** (0.240)	1.138*** (0.259)	1.079*** (0.255)	0.768** (0.348)
Vertical	0.588*** (0.124)	0.628*** (0.126)	0.682*** (0.136)	0.470** (0.222)
Area	0.0579 (0.108)	0.0380 (0.112)	0.026 (0.157)	-0.002 (0.107)
Snowfall	1.054 (0.885)	1.212 (0.932)	2.202** (0.839)	1.589** (0.710)
Snowmaking	0.110*** (0.0259)	0.120*** (0.0279)	0.179*** (0.042)	0.126** (0.061)

Note:

(1) Average (after-tax) ticket price is used to compute the marginal values of the characteristics for the semi-log model.

(2) Standard errors are in parentheses.