A Hedonic Price Model to Recover Marginal Willingness to Pay for Product Attributes in the Presence of Market Power

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Abstract

This study employs a hedonic price framework to estimate consumers' marginal willingness to pay for product attributes in imperfectly competitive markets. Our approach allows for the joint estimation of both price-cost markups and marginal values of product attributes under the popular semi-log specification, improving both the applicability and reliability of empirical hedonic valuation studies. Applying this new empirical strategy to analyze US lift ticket prices, our results reveal an estimated price-cost ratio between 1 and 2, with pass-sharing arrangements further amplifying this markup. Ignoring market power can bias the hedonic valuation of product attributes.

JEL Codes: Q51, L83

Key Words: Hedonic Method, Imperfect Competition, Taxation, Price-Cost Markup, Valuation of Ski Resort Characteristics

doi:10.3368/le.101.3.051124-0042R

1. Introduction

This study is motivated by a hidden issue in the application of the hedonic method for recovering consumers' marginal values for environmental (public) goods in the nonmarket valuation literature. As a primary tool for indirect valuation, the hedonic price method derives the economic value of an environmental (public) good from observed prices of related private goods. While widely used, most empirical applications of the first-stage hedonic price regression neglect how market power affects hedonic estimates. This study aims to develop simple yet theoretically consistent empirical hedonic price models capable of recovering marginal values of product attributes for products sold in imperfectly competitive markets. We present an analytical framework enabling the simultaneous estimation of price-cost markups and marginal values of product attributes within the commonly used semi-log specification of the hedonic price model.

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. In this setting, the partial derivatives of the hedonic price function with respect to product attributes represent the marginal values of those attributes. This insight underpins the hedonic method as a powerful, reduced-form empirical tool for recovering consumers' marginal values of product attributes. Many valuation studies have applied Rosen's framework. For example, hedonic property value analysis has been extensively used to estimate the economic value of air quality (e.g., Nelson, 1978; Li and Brown, 1980; Smith and Huang, 1995; Chattopadhyay, 1999; Chay and Greenstone, 2005; Huang, 2010; Bajari et al., 2012; Parmeter and Pope, 2013; and Bishop et al., 2020). The resulting consumer welfare calculations demonstrate the potential of this methodology to influence environmental policy.

However, differentiated products are seldom sold in purely competitive markets because production differentiation grants firms market power, enabling them to price above marginal costs. Feenstra (1995) demonstrates that this price-cost markup becomes embedded within hedonic price regressions under imperfect competition. In the case of a linear hedonic price function, coefficients still reflect the marginal values of product attributes, aligning with Rosen's (1974) results. Yet, with the common log-linear (semi-log) form, the price-cost ratio is embedded in the coefficient of each attribute. For example, $lnP = \alpha + \left(\frac{P}{C}\right)\gamma'\mathbf{z}$, where P is the price of a differentiated product, C is the marginal cost of production, and $\mathbf{z}$ is the vector of product attributes. The coefficient of each product attribute consists of two components: the marginal value of the attribute (γ) and the price-cost ratio $\left(\frac{P}{C}\right)$. Consequently, the partial derivatives of the equilibrium hedonic price equation no longer directly represent marginal values. Ignoring this embedded price-cost ratio can lead to biased estimation of the marginal values of product attributes, as also noted by Pakes (2003).

Feenstra's (1995) theoretical insights pose challenges for empirical implementation, particularly as the price-cost ratio is embedded in the coefficients of all explanatory variables in semi-log hedonic price models. Taylor and Smith (2000) propose a two-step empirical approach to first estimate the price-cost markup via residual demand estimation and then use this estimated markup to recover the marginal values of product attributes from a separately estimated hedonic price equation. Oktem and Huang (2011) employ the same two-step approach to estimate the property tax shifts from owners to renters in a rental housing market in the New Hampshire

Lakes Region. However, estimating residual demand models necessitates substantially greater data collection efforts and further limiting assumptions of the demand faced by firms.

Because the majority of applications of the hedonic method in environmental valuation can more or less be assumed pure competition, the theoretical issue of imperfect competition is often assumed away in the first-stage analysis of hedonic price models.[1] The reality is that market power can be nontrivial in some markets; for instance, the US ski industry is dominated by Vail Resorts and Alterra Mountain Company (Flaherty, 2023). Many researchers employ innovative approaches to construct proxy variables for addressing market power effects in hedonic price models (e.g., Aguiló, Alegre, and Sard, 2003; Harding, Rosenthal, and Sirmans, 2003; Cotteleer, Gardebroek, and Luijt, 2008; Firgo and Kügler, 2018). However, the semi-log hedonic specification inextricably bundles marginal values of product attributes with price-cost markups (Feenstra, 1995). Failing to account for this factor may lead to biased estimates of the economic values of product attributes in hedonic price analyses.

This study aims to improve the hedonic valuation method by relaxing the assumption of pure competition within the commonly used semi-log specification. Our theoretical analysis offers novel insights into the empirical specifications of hedonic price models under imperfect competition. We explicitly model shifts of the underlying demand curve, enabling the identification of price-cost markups within the equilibrium price analysis. This framework allows for direct testing and estimation of the price-cost ratio from a semi-log hedonic price equation, facilitating a straightforward calculation of the marginal values of product attributes. Our method draws upon identification conditions explored by Bresnahan (1982) and Lau (1982), where interactions between exogenous variables and price functions reveal the degree of market power. Specifically, we leverage taxation as an exogenous factor for identifying the price-cost ratio.

We conduct Monte Carlo simulations to assess the effectiveness of our empirical strategies. These simulations demonstrate that failing to account for imperfect competition can lead to substantial biases in the estimated marginal values of product attributes. By leveraging taxes as an exogenous shifter, our theoretically consistent specifications outperform standard hedonic price models, even when there is some misspecification in the functional form or production technology. We apply these new empirical strategies to analyze lift ticket prices in the US ski industry. Our estimation results reveal an estimated price-cost ratio between 1 and 2, with pass-sharing arrangements further amplifying this markup. Furthermore, we find that the hedonic valuation method for recovering marginal values of product attributes can be potentially biased if market power is not addressed.

The remainder of the paper is organized as follows. Section 2 extends Feenstra’s (1995) theoretical model, incorporating taxation under both linear and semi-log specifications to provide an empirical framework for addressing market power in hedonic price models. Section 3 presents a Monte Carlo simulation study to evaluate the performance of our proposed empirical strategies against standard empirical hedonic models. Section 4 applies this framework to a case study of the US ski industry, analyzing real-world price data and interpreting the empirical findings. The final section concludes.

2. Nash Equilibrium Hedonic Prices, Taxation, and Price-Cost Markup

Building upon Feenstra’s (1995) innovative work, we present a theoretical framework for a hedonic price model that incorporates taxes levied on consumers in an imperfectly competitive market. Suppose that a tax, T, is imposed on consumers. For example, T can be a sales tax that is itemized and added on top of the product price at the time of purchase.[2]

Suppose that product *j* is differentiated by a vector of characteristics $\boldsymbol{z}_j \in R_+^K$. Let P_j denote the price of product *j* charged by producers and T_j a tax levied on consumers as a percentage of P_j. This means that the total price of product *j* paid by consumers, denoted as $\tilde{P}_j$, is equal to $P_j(1+T_j)$, while the price received by producers remains P_j.[3] Due to this taxation, there is a gap between the price paid by consumers ($\tilde{P}_j$) and the price received by producers ($P_j = \tilde{P}_j \frac{1}{1+T_j}$).

Consumption Decisions

Feenstra's (1995) hedonic model is built on the assumption that individual behavior can be aggregated to a representative consumer who interacts with monopolistic firms in the consumption decisions of all differentiated goods. This facilitates the construction of the hedonic price equations, illustrating how non-competitive markets affect the ability of the hedonic regression to reveal the marginal values of product characteristics. Specially, assume there are *M* consumers, choosing over a fixed number of product varieties, $j = 1, \ldots, N$. The utility obtained by an individual from consuming product *j*, while spending the remaining income on the numeraire good, can be written in the following indirect form:

$$V_j = ln\phi_0(y) - ln\phi_j\left(\tilde{P}_j, \boldsymbol{z}_j\right) + e_j, \qquad j = 1, \ldots, N, \qquad [1]$$

where y denotes the individual's income, $\phi_j\left(\tilde{P}_j, \boldsymbol{z}_j\right)$ can be interpreted as a quality-adjusted price of product *j* (a strictly increasing function of $\tilde{P}_j$), and e_j is a random variable reflecting unobserved features of the products or the utility function. The quantity of each product variety can be chosen freely, and consumers will choose the product variety that offers the highest utility. This utility function [1] includes the linear random utility model and the CES model from Anderson, de Palma, and Thisse (1992) as special cases.

The random component (e_1, …, e_N) is assumed to follow a generalized extreme value distribution. Built on the work of McFadden (1978, 1983), Feenstra (1995) shows that this distributional assumption, along with the individual utility specified in [1], ensures the existence of an aggregate indirect utility function consistent with individual utility maximization: $V\left[\phi_1\left(\tilde{P}_1, \boldsymbol{z}_1\right), \dots, \phi_N\left(\tilde{P}_N, \boldsymbol{z}_N\right), Y\right]$, where $Y = M \cdot y$ denotes total income.[4] This aggregate indirect utility function can then be used to derive the market demand for each product variety, providing demand information to monopolistic firms when formulating their production and pricing decisions.

It is important to note that a key feature of such an aggregate utility function is the weak separability of ($\tilde{P}_j, \boldsymbol{z}_j$) across product varieties. The only source of heterogeneity across consumers comes from the additive random term in utility, which is a direct result of the individual utility specification in [1]. This is a limitation of the current framework. Incorporating heterogenous preferences for the amenities $\boldsymbol{z}$ is a fertile area for future research.

Production Decisions

With this framework, we can describe the profit maximization problem of a monopolistic firm selling product *j* as follows:[5]

$$\max_{\tilde{P}_j, \boldsymbol{z}_j} \left[\tilde{P}_j \frac{1}{1+T_j} - C_j\left(\boldsymbol{z}_j\right)\right] X_j\left(\tilde{P}_j, \boldsymbol{z}_j;\ \tilde{P}_{-j}, \boldsymbol{z}_{-j}\right), \qquad j = 1, \dots, N. \qquad [2]$$

Here, X_j represents the market demand for product *j* given the prices ($\tilde{P}_{-j}$) and characteristics ($\boldsymbol{z}_{-j}$) of other products. C_j denotes the cost of producing one unit of product *j*, which depends on its specific characteristics. The firm chooses the price of the product paid by consumers ($\tilde{P}_j$) and the vector of product characteristics ($\boldsymbol{z}_j$) to maximize profit.[6]

Given the existence of an aggregate indirect utility function, $V\left[\phi_1\left(\tilde{P}_1, \boldsymbol{z}_1\right), \ldots, \phi_N\left(\tilde{P}_N, \boldsymbol{z}_N\right), Y\right]$, we can use Roy's Identity to derive the corresponding market demand:

$$X_j = -\frac{\partial V / \partial \tilde{P}_j}{\partial V / \partial Y} = -\frac{\partial \phi_j}{\partial \tilde{P}_j} \frac{\partial V / \partial \phi_j}{\partial V / \partial Y}. \qquad [3]$$

To simplify notation, define $q_j = \phi_j\left(\tilde{P}_j, \boldsymbol{z}_j\right)$. Inverting this quality-adjusted price function yields $\tilde{P}_j = \tilde{\pi}_j\left(q_j, \boldsymbol{z}_j\right)$. Then, $\frac{\partial \phi_j}{\partial \tilde{P}_j}$ in [3] can be expressed as $\left(\frac{\partial \tilde{\pi}_j}{\partial q_j}\right)^{-1}$. Let $\left(\tilde{P}_j^*, \boldsymbol{z}_j^*\right)$ denote the Nash equilibrium price and product characteristics at which the profits of the firms are maximized. Then, q_j^*, defined as $\phi\left(\tilde{P}_j^*, \boldsymbol{z}_j^*\right)$, is the quality-adjusted price of product *j* at the Nash equilibrium. Holding q_j constant at q_j^* fixes the demand for all products other than variety *j*, leaving all arguments in *V* unaffected. As a result, the value of $\frac{\partial V / \partial \phi_j}{\partial V / \partial Y}$ evaluated at q_j^* is also fixed, and any change in X_j can be solely attributed to the change in $\left(\frac{\partial \tilde{\pi}_j}{\partial q_j}\right)^{-1}$. This allows us to simplify the firm's profit-maximization problem in [2] as follows:

$$\max_{\boldsymbol{z}_j} \left[\tilde{\pi}_j\left(q_j^*, \boldsymbol{z}_j\right) \frac{1}{1 + T_j} - C_j\left(\boldsymbol{z}_j\right)\right] \left(\frac{\partial \tilde{\pi}_j\left(q_j^*, \boldsymbol{z}_j\right)}{\partial q_j}\right)^{-1}. \qquad [4]$$

Once the functional form of the marginal cost function, $C_j(\cdot)$, is specified, we can derive the equilibrium price function – expressed in terms of $\boldsymbol{z}_j$ and T_j – by solving the profit maximization problem specified in [4]. Following Feenstra (1995), we consider both linear and semi-log marginal cost functions and derive their corresponding equilibrium price functions. These results are summarized in Proposition 1.

Proposition 1:

Let $\tilde{\pi}_j(q_j, \boldsymbol{z}_j)$ take the general form $f_j(q_j, \boldsymbol{z}_j) + g_j(\boldsymbol{z}_j)$, where $f_j(q_j, \boldsymbol{z}_j)$ is homogeneous of degree one in $\boldsymbol{z}_j$.

(a) If the marginal cost function is a linear function of production characteristics $\boldsymbol{z}_j$ ($C_j = \beta_0 + \sum_{k=1}^{K} \beta_k z_{jk} + v_j$), the equilibrium price function derived from [4] is:

$$P_j = \beta_0 + \sum_{k=1}^{K} \gamma_{jk} z_{jk}(1 - \hat{T}_j) + v_j, \quad [5]$$

where $\hat{T}_j = \frac{T_j}{1+T_j}$ is a transformed tax variable; $\gamma_{jk} = \frac{\partial \tilde{\pi}_j(q_j^*, \boldsymbol{z}_j^*)}{\partial z_{jk}}$ denotes the marginal value of z_{jk}; and v_j is a random error term capturing all other factors influencing the cost.

(b) If the marginal cost function is a semi-log function of $\boldsymbol{z}_j$ ($lnC_j = \beta_0 + \sum_{k=1}^{K} \beta_k z_{jk} + v_j$), the equilibrium price function derived from [4] is:

$$ln\tilde{P}_j = \beta_0 + \sum_{k=1}^{K} \frac{\tilde{P}_j}{C_j} \delta_{jk} z_{jk}(1 - \hat{T}_j) + \frac{\tilde{P}_j}{C_j} \hat{T}_j + v_j \,, \quad [6]$$

where $\delta_{jk} = \frac{\partial ln\tilde{\pi}_j(q_j^*, \boldsymbol{z}_j^*)}{\partial z_{jk}} = \frac{\partial \tilde{\pi}_j}{\partial z_{jk}} \frac{1}{\tilde{P}_j}$, so that the marginal value of z_{jk} is $\delta_{jk}\tilde{P}_j$.

The proof of Proposition 1 is provided in Appendix A. Part (a) of Proposition 1 states that with a linear marginal cost function, the price received by the firm (P_j) is a linear function of $z_{jk}(1 - \hat{T}_j)$, for k = 1,…, K. The transformed tax variable ($\hat{T}_j$) interacts only with the product characteristics in the price function. Importantly, the coefficient of $z_{jk}(1 - \hat{T}_j)$ directly reflects the marginal value of product attribute z_{jk}. The overall price impact of taxation depends on the levels of the product characteristics $\boldsymbol{z}_j$. For the linear cost function, market power exercised by firms cannot be determined from the hedonic price equation [5] alone.

Part (b) of Proposition 1 derives the semi-log equilibrium price function for product j under imperfect competition, based on a semi-log marginal cost function in terms of product characteristics $\boldsymbol{z}_j$. Note that the left-hand-side variables in price equations [5] and [6] are different. $\tilde{P}_j$ is the total price paid by consumers, including taxes, and P_j is the actual price received by producers, where $P_j = \frac{1}{1+T_j}\tilde{P}_j$. The transformed tax variable ($\hat{T}_j$) enters the price function [6] both interactively with $\boldsymbol{z}_j$ and independently, and its coefficient is the price-cost ratio. In [6] the coefficient of the transformed characteristics variable, $z_{jk}(1-\hat{T}_j)$, is $\frac{\tilde{P}_j}{C_j}$ times δ_{jk}. The marginal effect of $z_{jk}(1-\hat{T}_j)$ on the (log) product price is the marginal value of the characteristics, scaled up by the price-cost ratio. Moreover, with market power, a tax also helps the firm raise the price by $\frac{\tilde{P}_j}{C_j}$ times $\hat{T}_j$. This analytical result is empirically important because the marginal value of the characteristics can be recovered as the coefficient of the transformed characteristics variable divided by the coefficient of the transformed tax variable.

Proposition 1 shows the theoretically consistent specification of the equilibrium hedonic price equations under imperfect competition for two functional forms commonly adopted in empirical analysis. The theoretical results of Proposition 1 provide a means to appropriately account for market power when using the hedonic method to estimate marginal values of product attributes. As shown, the hedonic price equations [5] and [6] in Proposition 1 differ markedly from the price functions typically used in the hedonic valuation literature with an implicit or explicit assumption of pure competition. To highlight the importance of incorporating market power in the empirical specification of the hedonic valuation method for recovering marginal values of product attributes, a Monte Carlo simulation study is conducted and presented in the next section.

3. Monte Carlo Simulation

The analytical results presented in Section 2 provide guidance for the empirical specification of hedonic price equations under imperfect competition. Equations [5] and [6] illustrate the theoretically consistent specifications of the equilibrium hedonic price models for linear and semi-log marginal cost functions, respectively. In this section, we present a simulation study of hedonic valuation under imperfect competition. The purpose is to compare the standard hedonic approach, which assumes pure competition, with the hedonic price models that explicitly account for potential market power, as discussed in Section 2.

Design of the Imperfectly Competitive Market for Simulation

On the demand side of the market, assume there are *M* individuals and *N* product varieties. Each individual consumes a variable number of units x_j of product *j* and spends remaining income on the numeraire good, x_0. We model individual utility for consuming product *j* using the following threshold Cobb-Douglas function:[7]

$$U_j = \alpha ln\left(x_0 - x_j z_j^{\varphi}\right) + ln\left(x_j z_j\right) + e_j, \;\; j = 1, \dots, N, \qquad [7]$$

where z_j indicates the quality (characteristic) of product *j*; α and φ are parameters indicating the relative importance of x_0 and x_j to the consumer. The random component in the utility function, e_j, is assumed to follow an extreme value distribution with the following cumulative distribution function:

$$F_j(e_j) = exp\left\{-exp\left[-\left(\frac{e_j}{\mu} + k\right)\right]\right\}, \qquad [8]$$

where μ is a scale parameter and k is set to equal Euler's constant ($k \approx 0.5772$) so that the mean of e_j is zero. For each *j*, each individual maximizes [7] subject to the budget constraint, $x_0 + \tilde{P}_j x_j = y$, which yields an indirect utility function as follows:

$$V_j = (1+\alpha)ln(y) - ln\left(\frac{\tilde{P}_j + z_j^{\varphi}}{z_j}\right) + b + e_j, \qquad [9]$$

where $b = \alpha ln(\alpha) - (1+\alpha)ln(1+\alpha)$. Note that $\tilde{P}_j$ and z_j are "bundled" together in the above indirect utility function. Let $q_j = \frac{\tilde{P}_j + z_j^{\varphi}}{z_j}$. q_j can be interpreted as the quality-adjusted price of product *j*, since any changes in z_j will not affect the utility level once q_j is held constant.[8] By inverting quality-adjusted price function q_j, we obtain $\tilde{P}_j = \tilde{\pi}_j(q_j, z_j) = q_j z_j - z_j^{\varphi}$. Following McFadden (1978, 1983), we construct an aggregate utility function by summing each individual's expected value of maximum utility:

$$V = M(1+\alpha)\ln\left(\frac{Y}{M}\right) + M\mu\ln\left[\sum_{i=1}^{N}\left(\frac{\tilde{P}_i + z_i^{\varphi}}{z_i}\right)^{-1/\mu}\right]. \qquad [10]$$

Here $Y = y \cdot M$. From Roy's identity, the aggregate demand functions can be derived from the above aggregate utility function:[9]

$$X_j(\tilde{P}_j, z_j; \tilde{P}_{-j}, z_{-j}) = \frac{Y}{(\tilde{P}_j + z_j^{\varphi})(1+\alpha)}\left\{\frac{\left(\frac{\tilde{P}_j + z_j^{\varphi}}{z_j}\right)^{-1/\mu}}{\sum_{i=1}^{N}\left(\frac{\tilde{P}_i + z_i^{\varphi}}{z_i}\right)^{-1/\mu}}\right\}. \qquad [11]$$

On the supply side, we assume that each differentiated product *j* is produced by only one firm. As shown in Section 2, the profit maximization problem of a firm selling product *j* can be described as follows:

$$\max_{\tilde{P}_j, z_j}\left[\tilde{P}_i\frac{1}{1+T_j} - C_j(z_j)\right]X_j(\tilde{P}_j, z_j;\ \tilde{P}_{-j}, z_{-j}),\ \ j = 1, \ldots, N. \qquad [12]$$

All terms in the profit function are the same as those defined in Section 2. Next, we derive the first-order conditions for the firm's profit maximization problem [12] as follows:

$$[\tilde{P}_j] \Longrightarrow \frac{C_j(z_j)}{\tilde{P}_j} = \frac{1}{1+T_j}\frac{1+\varepsilon_j(\tilde{P},z)}{\varepsilon_j(\tilde{P},z)}, \qquad [13]$$

$$[z_j] \Longrightarrow \frac{\partial C_j(z_j)}{\partial z_j} = \left[\frac{1}{1+T_j}\frac{\tilde{P}_j}{z_j} - \frac{C_j(z_j)}{z_j}\right]\eta_j(\tilde{P},z), \qquad [14]$$

where $\varepsilon_j(\tilde{P},z) = \frac{\partial X_j(\tilde{P}_j,z_j;\tilde{P}_{-j},z_{-j})}{\partial \tilde{P}_j}\frac{\tilde{P}_j}{X_j(\tilde{P}_j,z;\tilde{P}_{-j},z_{-j})}$, $\eta_j(\tilde{P},z) = \frac{\partial X_i(\tilde{P}_j,z_j;\tilde{P}_{-j},z_{-j})}{\partial z_j}\frac{z_j}{X_j(\tilde{P}_j,z_j;\tilde{P}_{-j},z_{-j})}$, and $\tilde{P} = \{\tilde{P}_j, \tilde{P}_{-j}\}$.[10] $\tilde{P}_{-j}$ and z_{-j} denote the sets of prices and product characteristics of all other firms (excluding firm j), respectively.

Two functional forms, linear and semi-log, are employed for the marginal cost function $C_j(z_j)$. The resulting first-order conditions under each of the two cost functions are summarized as follows.

Specification 1: Linear marginal cost function $C_j(z_j) = \beta_0 + \beta_1 z_j + v_j$.

In this case, the first-order conditions of the firm's profit maximization problem can be simplified and rearranged as follows.

$$z_j = \frac{-\eta_j(\tilde{P},z)\cdot(\beta_0 + v_j)}{\beta_1\left(1+\varepsilon_j(\tilde{P},z)+\eta_j(\tilde{P},z)\right)}, \qquad [15]$$

$$\tilde{P}_j = (1+T_j)\frac{\varepsilon_j(\tilde{P},z)}{1+\varepsilon_j(\tilde{P},z)}(\beta_0+\beta_1 z_j + v_j), \qquad [16]$$

Given our consumer preference structure, the true marginal value of z_j is $\frac{\partial \tilde{\pi}_j}{\partial z_j} = q_j - \varphi z_j^{\varphi-1}$.

Specification 2: Semi-log marginal cost function $lnC_j(z_j) = \beta_0 + \beta_1 z_j + v_j$.

In this case, the first-order conditions of the firm's profit maximization problem can be shown as follows:

$$z_j = \frac{-\eta_j(\tilde{P}, z)}{\beta_1\left(1 + \varepsilon_j(\tilde{P}, z)\right)}, \quad [17]$$

$$\tilde{P}_j = (1 + T_j)\frac{\varepsilon_j(\tilde{P}, z)}{1 + \varepsilon_j(\tilde{P}, z)} e^{\beta_0 + \beta_1 z_j + v_j}, \quad [18]$$

Given our consumer preference structure, it can be shown that $\frac{\partial ln\tilde{\pi}_j}{\partial z_j} = \frac{q_j - \varphi z_j^{\varphi-1}}{q_j z_j - z_j^{\varphi}}$, which is the true marginal value of z_j expressed as a semi-elasticity.

The above first-order conditions for firms, along with the derived demand equations, determine the equilibrium values of prices and product characteristics. These ultimately depend on the distributional assumption of v_i, the values of five model parameters (N, β_0, β_1, μ, φ), and the tax rate (T_j). In the simulation, for each cost function specification, we devise four scenarios of parameter values. Table 1 summarizes these four scenarios (S1-S4) in which each scenario consists of one varying parameter across simulated datasets to help examine the stability of the estimation results.

<<Table 1 about here>>

For each scenario, we generate 500 different datasets, each with a sample size of 200. For each dataset, we assume there are 25 groups and 8 firms in each group. Tax rates vary across groups and datasets.[11] The price-cost ratios across firms are designed to range between 1 and 2.

Empirical Models for Comparison in Simulation

In line with common practice in the hedonic price literature, we employ a fixed-parameter estimation strategy. However, as shown in price equations [5] and [6], both markups and marginal values of characteristics should vary across product varieties. The coefficient of $z_{jk}(1 - \hat{T}_j)$ in equation [5] is not a fixed parameter, and the same holds for the coefficients of $z_{jk}(1 - \hat{T}_j)$ and $\hat{T}_j$ in equation [6]. In our data-generating process, each product variety j

(produced by one firm) has only one observation, making it impossible to estimate a model with j-specific coefficients. This is a common issue encountered by empirical researchers. Therefore, it is important to evaluate the performance of the fixed-parameter estimation strategy, even though it is not an unbiased estimation method.[12] The purpose is to compare these coefficient estimates with the average of true marginal values of characteristics.

For datasets generated with the linear cost function, we first estimate and compare the following five empirical models:

M1 $\tilde{P}_j = \alpha_0 + \alpha_1 z_j + \varepsilon_j,$

M2 $\tilde{P}_j = \alpha_0 + \alpha_1 z_j + \alpha_2 T_j + \varepsilon_j,$

M3 $P_j = \alpha_0 + \alpha_1 z_j + \varepsilon_j,$

M4 $P_j = \alpha_0 + \alpha_1 z_j + \alpha_2 T_j + \varepsilon_j,$

M5 $P_j = \alpha_0 + \alpha_1 z_j (1 - \hat{T}_j) + \varepsilon_j$, where $\hat{T}_j = \frac{T_j}{1+T_j}$

As defined above, $\tilde{P}_j$ is the total price paid by consumers, including taxes, while $P_j = \frac{1}{1+T_j}\tilde{P}_j$ is the actual price received by firms. The coefficient α_1 captures the average marginal value of characteristics, with the corresponding true value for comparison given by $\frac{1}{N}\sum_{j=1}^{N} \partial\tilde{\pi}_j / \partial z_j$. Models M1 and M3 are commonly used empirical specifications that do not consider tax effects or market power, while M2 and M4 include the tax variable as a simple additive term, which does not conform to the analytical results presented in Section 2. Model M5 takes into account the impacts of taxation and imperfect competition, based on our theoretical results.

For datasets generated with the semi-log cost function, we follow the same approach and estimate a parallel set of five empirical models:

M6 $lnP_j = \alpha_0 + \alpha_1 z_j + \varepsilon_j$,

M7 $lnP_j = \alpha_0 + \alpha_1 z_j + \alpha_2 T_j + \varepsilon_j$,

M8 $ln\tilde{P}_j = \alpha_0 + \alpha_1 z_j + \varepsilon_j$,

M9 $ln\tilde{P}_j = \alpha_0 + \alpha_1 z_j + \alpha_2 T_j + \varepsilon_j$,

M10 $ln\tilde{P}_j = \alpha_0 + \alpha_1 z_j(1 - \hat{T}_j) + \alpha_2 \hat{T}_j + \varepsilon_j$, where $\hat{T}_j = \frac{T_j}{1+T_j}$.

Models M6-M9 are common semi-log hedonic price models that do not explicitly account for potential market power exercised by firms under imperfect competition. In these models, the coefficient α_1 captures the average marginal value of characteristics (measured as a semi-elasticity), with the corresponding true value for comparison being $\frac{1}{N}\sum_{j=1}^{N} \partial ln\tilde{\pi}_j/\partial z_j$. In contrast, Model M10 is specified to closely resemble the theoretical model given in [6]. Consequently, the average marginal value of characteristics (measured as a semi-elasticity) in Model M10 is expressed as α_1/α_2 because the price-cost ratio is embedded in the coefficients of the resulting semi-log price equation, as shown in [6].

Finally, to examine the consequences of functional form misspecifications – specifically the mismatch between the empirical model and the true underlying model – we also estimate the linear M1-M5 models using datasets generated under a semi-log cost function and estimate the semi-log M6-M10 models for datasets generated under a linear cost function. In addition, we examine two more sources of model misspecification in the data-generating process: (1) the true underlying cost function is a log-log function; and (2) marginal production costs vary with output.

Simulation Results

Figure 1 presents boxplots comparing the estimated marginal values of product characteristic z from the five linear hedonic price models (M1-M5) against the true values.[13] The figure shows that our theory-based empirical model, M5, consistently outperforms the other empirical models by producing estimated marginal values of z closest to the true values across all four parameter scenarios.[14]

<<Figure 1 about here>>

Figure 2 summarizes, in boxplots, the simulation results obtained from the five semi-log hedonic price models (M6-M10) when the true underlying cost function is semi-log. As shown in Figure 2, Model M10, which aligns with our analytical results, consistently yields the most accurate estimates of the average marginal value of z (expressed as a semi-elasticity) across all four parameter scenarios.[15]

<<Figure 2 about here>>

Next, we examine the performance of linear (semi-log) hedonic price models when the true underlying cost function is semi-log (linear). Appendix Figure B1 presents the simulation results for the linear models M1-M5 when the true underlying cost function is semi-log, while Appendix Figure B2 summarizes the results of the semi-log models M6-M10 when the true underlying cost function is linear. The boxplots show that both theory-based models, M5 and M10, are resilient against misspecification of functional forms. Compared to M10, M5 yields median estimates closer to the true median value, but M5's estimates have a much wider spread than those from M10. Given its advantage in estimating the price-cost ratio and its overall strong performance in simulations, the theory-based semi-log model M10 generally appears to be a more suitable choice for empirical hedonic price studies, particularly when imperfect competition is a concern.

As a robustness check, we examine the performance of hedonic price models when the true underlying cost function is a log-log function, specified as follows:

$$lnC_j(z_j) = \beta_0 + \beta_1 lnz_j + v_j. \quad [19]$$

The model comparison results are provided in Appendix Table C1. In the first panel, we assume empirical researchers focus on the linear specification, which does not align with the true underlying cost function [19]. Nevertheless, our proposed linear hedonic price model, M5, produces smaller normalized root mean squared errors (NRMSE; see the notes to Appendix Table C1 for the definition of NRMSE) than the conventional linear hedonic price models, M1-M4. If empirical researchers focus on the semi-log specification instead, our proposed semi-log hedonic price model, M10, also consistently performs better than the conventional semi-log hedonic price models.

In our theoretical derivation, the cost of producing one unit of product j, $C_j(z_j)$, depends only on the level of characteristics and not on output. This is a limitation in monopolistic competition setting. To address this, we modify the data-generating process by allowing the marginal cost of production to vary with output. Specifically, the firm's original profit maximization problem [12] is modified as follows:

$$\max_{\tilde{P}_j, z_j} \left[\tilde{P}_i \frac{1}{1+T_j} - C_j(z_j) X_j(\tilde{P}_j, z_j;\ \tilde{P}_{-j}, z_{-j}) \right] X_j(\tilde{P}_j, z_j;\ \tilde{P}_{-j}, z_{-j}),\ \ j = 1, \dots, N. \quad [20]$$

This introduces another source of model misspecification, and none of the empirical models M1-M10 consistently align with this new data-generating process. Appendix Table C2 summarizes the model comparison results. The first and second panels focus on the linear and semi-log specifications, respectively. Again, our proposed hedonic price models perform reasonably well compared to the conventional hedonic price models.

The simulation results show that our theory-based empirical models, constructed from equations [5] and [6], consistently outperform the standard empirical models that ignore imperfect competition by producing estimated marginal values that are closer to the true values. They are also more robust to misspecifications in functional forms or production technology than the standard models. While it is difficult to generalize the results from a Monte Carlo simulation study, our findings highlight the value of considering our proposed method, particularly when there is strong evidence suggesting that the market is not perfectly competitive. In the next section, we present a case study to demonstrate the empirical feasibility of our methodology.

4. A Study of Consumer Value for Ski Resort Amenities

We apply our new hedonic model specification to a study of pricing in the U.S. ski industry. We compiled data on lift ticket prices and characteristics of ski areas for the 2014-15 ski season.[16] In our dataset, 361 ski areas provide the necessary information, representing more than 80% of all operating ski areas in the U.S. during that period. For our empirical analysis, we divide ski areas into six regions (Mid-Atlantic, Midwest, New England, Rocky Mountains, Southeast, and West Coast) and control for regional differences by including regional dummy variables in all models.

The variable definitions and summary statistics for the ski areas are given in Table 2. Note that lift ticket pricing schemes vary across ski areas. Lift ticket prices can also differ by time of day or peak seasons within the same ski area. For consistency, we use the full-day lift ticket price as the dependent variable in all analyses, as this price is universally offered across ski areas.[17]

<<Table 2 about here>>

We include two weather-related variables in the analysis: annual snowfall in local areas and the percentage of total skiable area that can be covered with artificial snow. City-level sales tax rates are also included. Note that in the ski industry, sales tax may be either added to the listed lift ticket price or included in the list price. Some states exempt lift tickets entirely, classifying them as service products. Based on the listed price and specific tax collection practices, we construct two price variables for each ski area: the total price paid by skiers ($\tilde{P}$) and the actual price received by the ski area after deducting taxes ($P = \frac{1}{1+T}\tilde{P}$).[18]

Note that it is not uncommon for ski areas to share ski passes or be owned and operated by the same company.[19] This can streamline pricing and services across those ski areas. As shown in Table 2, 19.4% of the ski areas participate in pass-sharing arrangements, and 20.2% are owned by companies that operate multiple ski areas. These business practices may reinforce the market power of ski areas. Economic theory suggests that these practices can have two effects: (1) they may lower marginal costs through knowledge transfer or economies of scale within a larger network, and (2) they may enhance market power through reductions in direct competition or improvements in product quality that further differentiate their products in the market. The first effect could lower product prices while increasing price-cost markups, whereas the second effect could increase both product prices and price-cost markups. Our analysis incorporates ownership information and ski pass-sharing arrangements to account for these potential effects.[20]

Estimation and Results

We examine various hedonic price model specifications. Table 3 presents the estimation results for both linear and semi-log models.[21] Model 1 is a typical linear hedonic price equation that regresses prices on relevant explanatory variables, including the tax variable directly. Model 2 is a typical semi-log hedonic price equation, also including the tax variable directly. Neither

Model 1 nor Model 2 accounts for the impact of imperfect competition on the model specifications. Model 3 is constructed using Equation [5] to ensure that the empirical linear model specification aligns with our theoretical results under imperfect competition. According to Equation [5], the tax variable enters only interactively with other explanatory variables. Model 4 is specified according to theoretical results presented in Equation [6], where the tax variable enters the semi-log price equation both independently and interactively with other explanatory variables. Importantly, the coefficient of the (transformed) tax variable estimates the price-cost ratio.

<<Table 3 about here>>

Table 3 shows how the characteristics of ski areas influence lift ticket pricing. Notably, for the linear models, the estimated coefficient of the Lifts variable differs significantly between Models 1 and 3. For the semi-log models, the estimated coefficients of the Lifts, Distance and Snowmaking variables differ significantly between Models 2 and 4. This finding suggests that market power impacts pricing for both functional forms.

Several ski area features and snowfall levels have a positive impact on the pricing of ski lift tickets. Specifically, the number of trails, the number of lifts, elevation, and vertical drops all positively affect lift ticket prices. Natural snow also adds value, and all else being equal snowmaking facilities are desirable. The estimated coefficient of the tax variable is insignificant in the standard hedonic price models (Models 1 and 2). The qualitative results for the impact of ski area characteristics are broadly similar between the linear and semi-log models.

In Model 2 (a standard semi-log hedonic price model), the estimated coefficient of the tax variable is less than 1 and insignificant, even after controlling for regional fixed effects. In contrast, Model 4, using our theoretically consistent specification, produces a plausible coefficient estimate of the (transformed) tax variable. This coefficient represents the price-cost ratio, which is estimated to be approximately 1.5, indicating some markup in prices. Importantly, this price-cost ratio estimate allows us to recover the marginal values of ski area characteristics from the remaining coefficient estimates.

In addition, Table 3 shows insignificant coefficients for both the group-owned and pass-sharing dummy variables across all four models. To further examine the potential impact of these business practices on price-cost ratios, we introduce interaction terms with the transformed tax variable. The results are reported in Table 4. Model 6 in Table 4 reveals that ski areas with pass-sharing arrangements command significantly higher price markups. While Model 5 in Table 4 suggests a potential positive impact of group ownership on markups, this effect is not statistically significant. Model 7 in Table 4 confirms that pass-sharing arrangements, rather than group ownership, are the important driver of increased price-cost markups.

<<Table 4 about here>>

Our analysis highlights the market power enhancement created by pass-sharing "brand" effects in the ski industry. This aligns with Firgo and Kügler's (2018) findings that alliance ski resorts significantly overcharged for single-day lift tickets compared to non-alliance ski resorts in Austria during the 2011-2012 season. They also find that allowing alliance members to sell multiday tickets valid at all resorts leads to cooperative pricing for single-day tickets in Austria. Our empirical results provide clear evidence that pass-sharing significantly increases market power, leading to higher lift ticket prices.

Estimated Marginal Values of Ski Area Characteristics

The empirical analysis presented in Table 4 indicates potential price-cost markups in the ski industry, with pass-sharing arrangements potentially amplifying these markups. Table 5 reports the estimated marginal values of ski area characteristics derived from Models 3, 4 and 6 (see Tables 3 and 4). Recall that Model 3 is the theoretically consistent linear model with transformed independent variables that addresses potential market power, and the estimated coefficients are the marginal values of ski area characteristics. Semi-log Models 4 and 6 are specified following the analytical results of Equation [6]. The estimated marginal values from Models 4 and 6 are recovered by dividing each estimated coefficient by the estimated coefficient of the transformed tax variable and then scaling by the average price. From Model 6, we compute two sets of marginal values: one for ski areas that participate in pass sharing, and one for those that do not.

<<Table 5 about here>>

Several characteristics of ski areas, including the base elevation of the ski area, vertical drop of the mountain, number of trails, number of lifts, and the distance to the closest major city with an international airport, are valued significantly by visitors. The marginal values of natural snowfall and snowmaking ability are also positive and significant, as expected. Interestingly, the semi-log models generally produce lower estimated marginal values compared to the linear model, with natural snowfall and snowmaking abilities being notable exceptions.

By examining the two sets of estimated marginal values from Model 6, together with previous findings, we find that ski areas engaging in pass-sharing arrangements tend to charge higher prices, apply larger price markups, and associate with lower marginal values for their ski area characteristics.

5. Concluding Remarks

Empirical hedonic price studies for environmental valuation often overlook the potential impact of market power on pricing. In this study, we propose utilizing an available demand or supply shifter in the hedonic price equation to enable the simultaneous estimation of the price-cost markup and marginal values of product attributes. We specifically demonstrate the use of theory-based empirical specifications of linear and semi-log hedonic price models under imperfect competition. Instead of assuming away any potential market power, our approach provides a means to incorporate market power into empirical hedonic price analysis. This ultimately leads to more accurate estimation of marginal values for product attributes, including those related to environmental goods, using the hedonic method under imperfect competition.

In contrast to the reduced-form approach of the hedonic method used in the nonmarket valuation literature, the industrial organization literature often favors structural approaches. For example, Berry, Levinsohn, and Pakes (1995) take into account richer distributions of consumer tastes and present an analytical framework and estimation strategies to estimate both demand and supply equations for the automobile industry under various model specifications and market conditions. However, when the primary goal is to recover marginal values of product attributes, the hedonic method can be a convenient and advantageous empirical strategy.[22] It requires less data input and is less computationally demanding than structural approaches.

The role of taxation is closely examined in our analysis. Although the literature has well documented the empirical evidence of tax capitalization into property values (e.g., Gyourko and Tracy, 1991; Chattopadhyay, 1999; Chay and Greenstone, 2005), tax variables are often omitted in hedonic housing price equations. This is largely due to data limitations with single-jurisdiction studies, where tax rates offer little variation. In larger-scale studies of multiple cities, tax variables can be included. However, they are usually treated as traditional attributes in hedonic price models, added as separate explanatory variables. This approach may not be fully consistent with economic theory, particularly under imperfect competition. In this study, we show that, methodologically, taxes provide a means to identify price-cost markups to help recover the marginal values of product attributes with the hedonic method. Equally important, we also illustrate how to appropriately account for both direct and indirect effects of taxation (via interactions with other product attributes) on pricing within imperfectly competitive markets.

In our empirical study of pricing in the ski industry, we examine the impact of pass-sharing arrangements and group-owned ski areas on price-cost markups. This finding highlights the potential for heterogeneous market power across different organizational structures. Future research to empirically address these differential market power effects is warranted. In addition, our theoretical price equations clearly indicate that both markups and marginal values of characteristics should vary across products. A richer dataset with a more advanced econometric tool that goes beyond the fixed-parameter estimation strategy will be needed. Furthermore, while this paper proposes using taxation as a shifter to identify markups, it is important to acknowledge that this approach is not a panacea for the inherent challenges of hedonic analysis. Issues such as capitalization effects (e.g., Kuminoff and Pope, 2014) and the stability of the hedonic function (e.g., Taylor, 2003) can impact the effectiveness of this approach and warrant further investigation.

Acknowledgments

We are very grateful for the comments and suggestions from the editor, two anonymous referees, participants at the 6th World Congress of Environmental and Resource Economists (Gothenburg), and seminar participants at Academia Sinica, Jinan University, National Taiwan University, University of Macau, University of New Hampshire, Xiamen University, and Xi'an Jiaotong University. Any remaining errors are solely our own. Zhao acknowledges financial support from the National Natural Science Foundation of China (No. 71773102).

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Table 1: Four Scenarios of Parameter Values Used in the Simulation Analysis

Scenario	Parameters fixed in each dataset	Parameters varied across datasets
S1	β_1 = 0.5, μ = 0.5, φ = 2.5	β_0~ uniform(0.5, 1.5)
S2	β_0 = 1, μ = 0.5, φ = 2.5	β_1~ uniform(0.01, 1)
S3	β_0 = 1, β_1= 0.5, φ = 2.5	μ ~ uniform(0.01, 1)
S4	β_0 = 1, β_1= 0.5, μ = 0.5	φ ~ uniform(2, 3)

Notes:

(1) Assume that there are 25 groups with 8 firms in each group. N = 200.

(2) Tax rate T_j follows a uniform (0, 10%) distribution and varies across groups and datasets.

(3) The cost shock v_j follows a normal (0, 0.001) distribution and varies across firms and datasets.

(4) β_0 and β_1 are the parameters of a cost function. For a linear cost function, $C_j(z_j) = \beta_0 + \beta_1 z_j + v_j$. For a semi-log cost function, $lnC_j(z_j) = \beta_0 + \beta_1 z_j + v_j$.

Table 2: Summary Statistics of Ski Areas

Variable	Definition	Mean	S.D.
Lift Ticket Price	Full day lift ticket price at the window (after tax). US$	52.01	21.02
Beginner	Percentage of trails designated as of a beginner level.	27.75	11.14
Elevation	Elevation at the top of the mountain measured in hundreds of feet.	45.58	36.84
Vertical	Vertical drop of the mountain measured in hundreds of feet.	11.88	9.33
Trails	Number of trails.	41.65	37.12
Lifts	Number of operational non-rope tow lifts at the mountain.	5.25	4.41
Area	Skiable area of the mountain measured in hundreds of acres.	6.03	9.09
Distance	Distance in miles to the closest major city with an international airport.	218.14	162.55
Snowfall	Average annual snowfall measured in hundreds of inches.	1.80	1.37
Snowmaking	Percentage of total skiable area that can be serviced by snowmaking equipment.	62.24	41.22
Tax	City sales tax rate levied on lift tickets.	3.33%	3.50%
Group-owned	A dummy indicator = 1 if a ski area is owned by a company that owns multiple ski areas.	20.2%	
Pass-sharing	A dummy indicator = 1 if a ski area participates in pass-sharing arrangements.	19.4%	

Notes:
(1) The time period is 2014-2015.
(2) Pass-sharing arrangements include the following: Epic Pass, Utah Gold Pass, Mountain Collective, MAX Pass, Powder Alliance, Rocky Mountain Super Pass, Gold Pass, and Power Pass.
(3) Data sources: see footnotes 16 and 20.

Table 3: Hedonic Price Regression Models

Not Considering Imperfect Competition			Considering Imperfect Competition		
	Model 1	Model 2		Model 3	Model 4
	Linear	Semi-Log		Linear	Semi-Log
Dep. Variable:	P	$ln\tilde{P}$	Dep. Variable:	P	$ln\tilde{P}$
Beginner	0.0728	6.91e-05	Beginner·(1-$\widehat{\text{Tax}}$)	0.0761	0.000115
	(0.0454)	(0.00107)		(0.0480)	(0.00104)
Elevation	0.117*	0.00308**	Elevation·(1-$\widehat{\text{Tax}}$)	0.116	0.00300**
	(0.0504)	(0.00102)		(0.0615)	(0.00108)
Vertical	0.848***	0.0142***	Vertical·(1-$\widehat{\text{Tax}}$)	0.842**	0.0143**
	(0.190)	(0.00345)		(0.222)	(0.00380)
Trails	0.123*	0.00200*	Trails·(1-$\widehat{\text{Tax}}$)	0.122*	0.00201*
	(0.0509)	(0.000940)		(0.0536)	(0.000972)
Lifts	1.299***	0.0283**	Lifts·(1-$\widehat{\text{Tax}}$)	1.397***	0.0296**
	(0.256)	(0.00911)		(0.246)	(0.00943)
Area	-0.122	-0.00172	Area·(1-$\widehat{\text{Tax}}$)	-0.115	-0.00147
	(0.149)	(0.00380)		(0.124)	(0.00360)
Distance	-0.0154*	-0.000316*	Distance·(1-$\widehat{\text{Tax}}$)	-0.0158*	-0.000328*
	(0.00623)	(0.000149)		(0.00658)	(0.000151)
Snowfall	0.773**	0.0431***	Snowfall·(1-$\widehat{\text{Tax}}$)	0.889**	0.0448***
	(0.290)	(0.00871)		(0.315)	(0.00940)
Snowmaking	0.0706**	0.00294***	Snowmaking·(1-$\widehat{\text{Tax}}$)	0.0767**	0.00314***
	(0.0245)	(0.000685)		(0.0221)	(0.000683)
Tax	-8.373	0.567	$\widehat{\text{Tax}}$		1.449**
	(8.554)	(0.335)			(0.394)
Group-owned	2.366	0.0201	Group-owned	2.278	0.0183
	(1.947)	(0.0256)		(2.031)	(0.0253)
Pass-sharing	1.783	-0.0171	Pass-sharing	1.896	-0.0126
	(3.234)	(0.0642)		(3.303)	(0.0668)
Regional dummies	Y	Y	Regional dummies	Y	Y
N	361	361	N	361	361
Adj. R-squared	0.770	0.660	Adj. R-squared	0.769	0.658

Notes:
(1) Cluster-robust standard errors at the regional level are reported in parentheses.
(2) $\widehat{\text{Tax}}$ = Tax/(1 + Tax).
(3) *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Semi-Log Models with Variations in Price-Cost Markups

	Model 5	Model 6	Model 7
Dep. Variable:		$ln\tilde{P}$	
Beginner·(1-$\widehat{T}$ax)	0.000144	0.000158	0.000159
	(0.00103)	(0.00105)	(0.00104)
Elevation·(1-$\widehat{T}$ax)	0.00302**	0.00317**	0.00317**
	(0.00106)	(0.00101)	(0.00103)
Vertical·(1-$\widehat{T}$ax)	0.0145**	0.0148***	0.0148***
	(0.00385)	(0.00364)	(0.00364)
Trails·(1-$\widehat{T}$ax)	0.00206*	0.00204*	0.00204*
	(0.000987)	(0.000979)	(0.000997)
Lifts·(1-$\widehat{T}$ax)	0.0295**	0.0295**	0.0295**
	(0.00911)	(0.00932)	(0.00907)
Area·(1-$\widehat{T}$ax)	-0.00158	-0.00174	-0.00174
	(0.00365)	(0.00363)	(0.00367)
Distance·(1-$\widehat{T}$ax)	-0.000332*	-0.000342*	-0.000342*
	(0.000149)	(0.000155)	(0.000153)
Snowfall·(1-$\widehat{T}$ax)	0.0443***	0.0429***	0.0429***
	(0.00887)	(0.00937)	(0.00920)
Snowmaking·(1-$\widehat{T}$ax)	0.00312***	0.00306***	0.00306***
	(0.000651)	(0.000683)	(0.000665)
$\widehat{T}$ax	1.367*	1.176**	1.176*
	(0.569)	(0.416)	(0.528)
Group-owned·$\widehat{T}$ax	0.383		0.00728
	(1.442)		(1.557)
Pass-sharing·$\widehat{T}$ax		1.001*	0.998**
		(0.489)	(0.385)
Group-owned	0.00594	0.0137	0.0135
	(0.0580)	(0.0257)	(0.0609)
Pass-sharing	-0.0172	-0.0524	-0.0524
	(0.0581)	(0.0654)	(0.0686)
Regional dummies	Y	Y	Y
N	361	361	361
Adj. R-squared	0.657	0.657	0.656

Notes:
(1) Cluster-robust standard errors at the regional level are reported in parentheses.
(2) $\widehat{T}$ax = Tax/(1 + Tax).
(3) *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Estimated Marginal Values of Characteristics of Ski Areas

	Linear Model	Semi-Log Model		
Empirical Model	Model 3	Model 4	Model 6	
			Pass-sharing = 0	Pass-sharing = 1
Beginner	0.0761	0.00414	0.00620	0.00559
	(0.0480)	(0.0375)	(0.0413)	(0.0367)
Elevation	0.116	0.108***	0.124***	0.112**
	(0.0615)	(0.0400)	(0.0401)	(0.0451)
Vertical	0.842**	0.513***	0.579***	0.522***
	(0.222)	(0.107)	(0.191)	(0.0918)
Trails	0.122*	0.0723	0.0799	0.0721*
	(0.0536)	(0.0500)	(0.0580)	(0.0423)
Lifts	1.397***	1.0644*	1.156	1.043***
	(0.246)	(0.603)	(0.741)	(0.370)
Area	-0.115	-0.0527	-0.0680	-0.0614
	(0.124)	(0.136)	(0.152)	(0.134)
Distance	-0.0158*	-0.0118**	-0.0134*	-0.0121**
	(0.00658)	(0.0060)	(0.00744)	(0.00497)
Snowfall	0.889**	1.608***	1.679***	1.514***
	(0.315)	(0.384)	(0.542)	(0.342)
Snowmaking	0.0767**	0.113**	0.120*	0.108***
	(0.0221)	(0.0541)	(0.0686)	(0.030)

Note:
(1) The marginal values of the characteristics of ski areas are defined as $\partial\tilde{\pi}_j/\partial z_{jk}$. The average ticket price ($\tilde{P}$) is used to compute these marginal values for the semi-log models.
(2) Models 3 and 4 are obtained from Table 3. Model 6 is obtained from Table 4.
(3) Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure Captions

Figure 1: Performance of Empirical Linear Hedonic Price Models

Notes:
(1) The underlying true cost function is a linear function.
(2) Model specifications (M1-M5) are provided in Section 3. Only Model M5 accounts for the impacts of taxation and imperfect competition.

Figure 2: Performance of Empirical Semi-Log Hedonic Price Models

Notes:
(1) The underlying true cost function is a semi-log function.
(2) Model specifications (M6-M10) are provided in Section 3. Only Model M10 accounts for the impacts of taxation and imperfect competition.

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[1] In the industrial organization literature, empirical methods have been developed to estimate unobservable price-cost ratios (e.g., Bresnahan, 1981; Feenstra and Levinsohn, 1995). While these methods are typically applied to analyze oligopolistic scenarios, they are not tailored to the specific requirements of nonmarket valuation. A more recent approach, developed by Bajari and Benkard (2005), incorporates both the first and second stages of hedonic price analysis to account for the impact of imperfect competition. In contrast, our study focuses on the first-stage hedonic regression, refining the reduced-form approach to provide a feasible method for simultaneously recovering both price-cost ratios and marginal values of product attributes within the commonly used semi-log specification.

[2] Any variable that shifts the demand or supply curve can be utilized in our theoretical analysis. In this paper, we focus on analytical results using a tax variable as a demand shifter. A more generalized analysis for a hedonic price model with taxes on both consumers and producers is available upon request.

[3] Our analytical results focus on ad valorem taxes (as fixed percentages of product prices) common in hedonic price applications. Similar results for per unit taxes (as fixed amounts levied on each unit of the product) are available upon request.

[4] Specifically, $V[\phi_1(\tilde{P}_1, \boldsymbol{z}_1), \dots, \phi_N(\tilde{P}_N, \boldsymbol{z}_N), Y] = M \cdot ln\phi_0(Y/M) + M \cdot lnG[\phi_1(\tilde{P}_1, \boldsymbol{z}_1)^{-1}, \dots, \phi_N(\tilde{P}_N, \boldsymbol{z}_N)^{-1}]$, where G is a non-negative function defined over R_+^K that satisfied the conditions provided in McFadden (1978, p.80; 1983, pp.227-228).

[5] We adopt the same assumption as in Feenstra (1995) that the marginal cost of producing variety j, $C_j(\boldsymbol{z}_j)$, is independent of output j and the outputs of other product varieties. A firm may sell J differentiated product varieties, and its profit maximization problem can be described as follows:

$$\max_{\{\tilde{P}_j, \boldsymbol{z}_j\}_{j=1}^{J}} \sum_{j=1}^{J} \left[\tilde{P}_j \frac{1}{1+T_j} - C_j(\boldsymbol{z}_j)\right] X_j(\tilde{P}_j, \boldsymbol{z}_j;\ \tilde{P}_{-j}, \boldsymbol{z}_{-j}).$$

Under this assumption, the resulting optimality conditions are identical to those obtained when each firm is assumed to produce only a single product variety.

[6] See Feenstra (1995) for a discussion of various conditions examined in Caplin and Nalebuff (1991) and Milgrom and Roberts (1990) that guarantee the existence of a pure-strategy Nash equilibrium.

[7] The individual utility function [7] is modified from an example given in Feenstra (1995). It satisfies all necessary aggregation conditions, ensuring the existence of a well-defined aggregate demand function.

[8] We can also define the quality-adjusted price as $q_j = ln\left(\frac{\tilde{P}_j+z_j^{\varphi}}{z_j}\right)$. In fact, any monotonic transformation of the quality adjusted price $q_j = \phi(\tilde{P}_j, z_j)$ will yield the same analytical results for the marginal values of product characteristics.

[9] Note that the aggregate demand functions [11] can be equivalently constructed by summing each individual's expected demand, $M \cdot x_j \cdot Prob[V_j = \max_{i=1,\dots,N} V_i]$. Our individual utility function is chosen to ensure the existence of an aggregate utility function that is consistent with individual utility maximization.

[10] According to the demand equation [11], $\varepsilon_j(\tilde{P}, z) = -\frac{1}{\mu}\frac{\tilde{P}_j}{\tilde{P}_j+z_j^{\varphi}} - \frac{\tilde{P}_j}{\tilde{P}_j+z_j^{\varphi}} + \frac{1}{\mu}\frac{\frac{\tilde{P}_j}{z_j}\left(\frac{\tilde{P}_j+z_j^{\varphi}}{z_j}\right)^{-(1+\mu)/\mu}}{\sum_{i=1}^{N}\left(\frac{\tilde{P}_i+z_i^{\varphi}}{z_i}\right)^{-1/\mu}}$, and $\eta_j(\tilde{P}, z) = \frac{-\varphi z_j^{\varphi}}{\tilde{P}_j+z_j^{\varphi}} + \frac{1}{\mu}\frac{\tilde{P}_j+(1-\varphi)z_j^{\varphi}}{\tilde{P}_j+z_j^{\varphi}} - \frac{1}{\mu}\frac{\tilde{P}_j+(1-\varphi)z_j^{\varphi}}{\tilde{P}_j+z_j^{\varphi}}\frac{\left(\frac{\tilde{P}_j+z_j^{\varphi}}{z_j}\right)^{-1/\mu}}{\sum_{i=1}^{N}\left(\frac{\tilde{P}_i+z_i^{\varphi}}{z_i}\right)^{-1/\mu}}$.

[11] Firms within the same group are subject to the same tax rate. Our proposed approach does not require tax variation across firms. As a robustness check, we also generate datasets with only 4 groups and 50 firms in each group. This modification does not change the qualitative conclusions of our simulation exercises.

[12] If a panel dataset is available, markups and marginal values of characteristics can be treated as random coefficients. The Swamy (1970) model is a useful starting point by assuming that these random coefficients are uncorrelated across product varieties and follow the same distribution over time. A literature review on more advanced random coefficient panel data models with less restrictive assumptions can be found in Hsiao and Pesaran (2008). In the case of a semi-log specification, the markup appears in both coefficients of $z_{jk}(1-\hat{T}_j)$ and $\hat{T}_j$, as shown in equation [6]. If treating the markup as a random coefficient, it is important to explicitly account for this structure instead of modeling the coefficients of $z_{jk}(1-\hat{T}_j)$ and $\hat{T}_j$ as two independent random coefficients.

[13] A boxplot is a graphical representation of a distribution. It includes a box, with a horizontal line inside indicating the median and the top and bottom edges denoting the third and first quartiles, respectively. Lines extend from the box, indicating the span of 1.5 times the interquartile range, with any dots beyond these lines considered as outliers.

[14] M5 can be equivalently rewritten as $\tilde{P}_j = \alpha_0 + \alpha_0 T_j + \alpha_1 z_j + (1+T_j)\varepsilon_j$. Moving from M2 to M5 involves two modifications to M2: (1) restricting the coefficients of the intercept and T_j to be the same; and (2) scaling the error term by $1+T_j$. To investigate the impact of these modifications, we estimate an intermediate model, M2a: $\tilde{P}_j = \alpha_0 + \alpha_0 T_j + \alpha_1 z_j + \varepsilon_j$. Comparing the performance of models M2, M2a, and M5 reveals that restriction (1) in M2 is the primary driver of improved model performance in estimating the marginal value of characteristics.

[15] The variance of v_j is set to be identical for both linear and semi-log cases. Its value is small to ensure the marginal cost is positive under the linear case. However, this restriction is not necessary for the semi-log case. To examine the robustness of our simulation results, we conduct additional simulation by gradually increasing the variance of cost shocks from 0.001 to 2. Model M10, which explicitly accounts for taxation and imperfect competition, consistently and substantially outperform the other models that neglect these factors. For the linear case, when the variance of cost shocks is doubled, M5 continues to outperform the conventional hedonic models, but the performance gap between M5 and the second-best model narrows as the variance of cost shocks continues to increase. These additional simulation results are available upon request.

[16] Our data primarily comes from the White Book of Ski Areas website (http://www.whitebookski.com), supplemented by information from OnTheSnow (https://www.onthesnow.com), Gondyline (https://www.gondyline.com), Ski Resorts Guide (http://www.skiresorts.org), and individual ski area websites.

[17] Alternative options for the dependent variable could include half-day, weekday and peak period passes. However, not all ski areas offer these different pricing options.

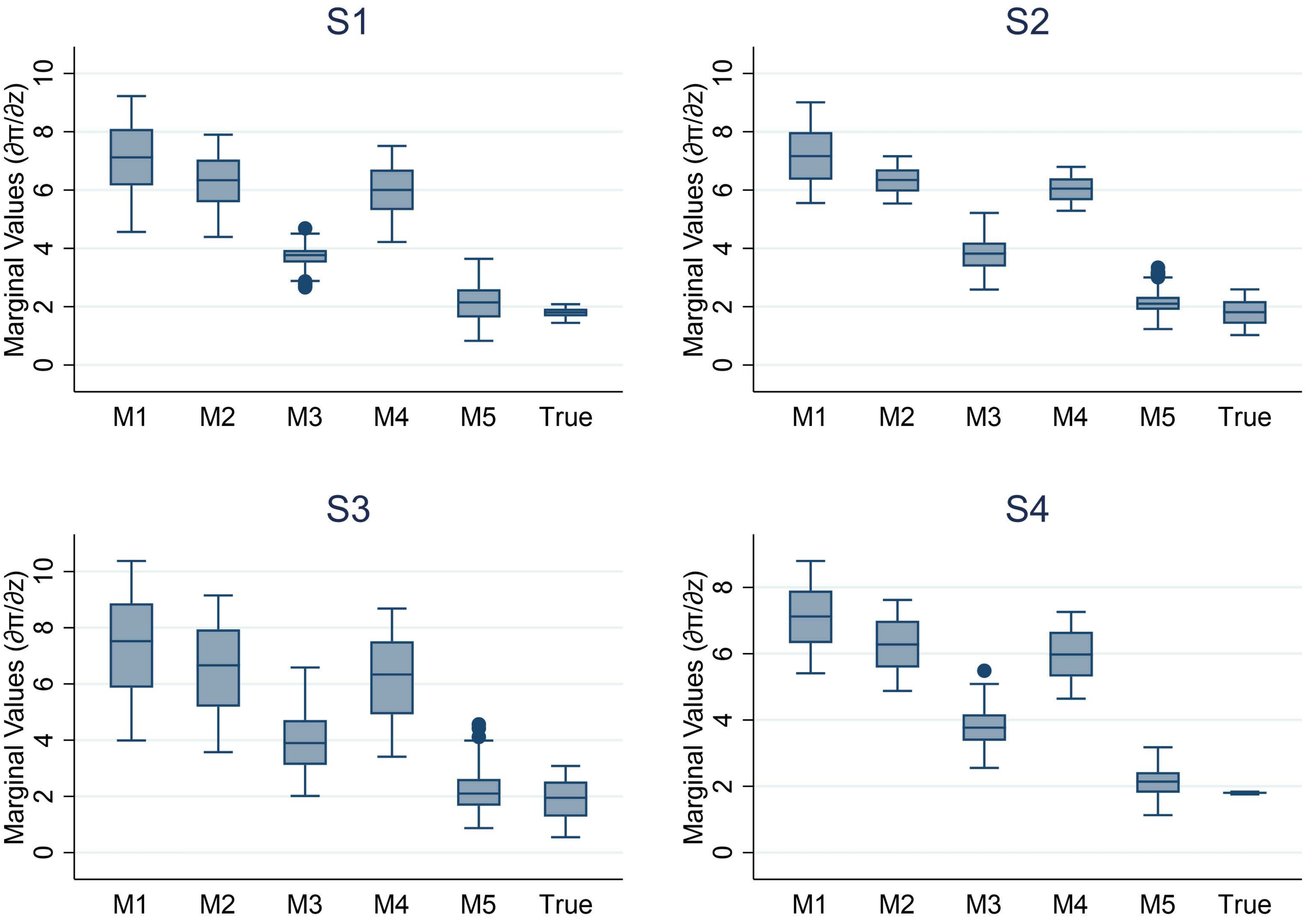
[18] In this case study, the empirical identification strategy relies on variation in taxes. Given the need for variation in taxes and the limited number of ski areas in each region, it is not feasible to estimate price equations by region. All ski areas are pooled together to estimate a single price equation. This approach necessitates the assumption of a single market for the ski industry, despite the inherent limitations. To account for regional differences, regional dummies are included in the regression analysis.

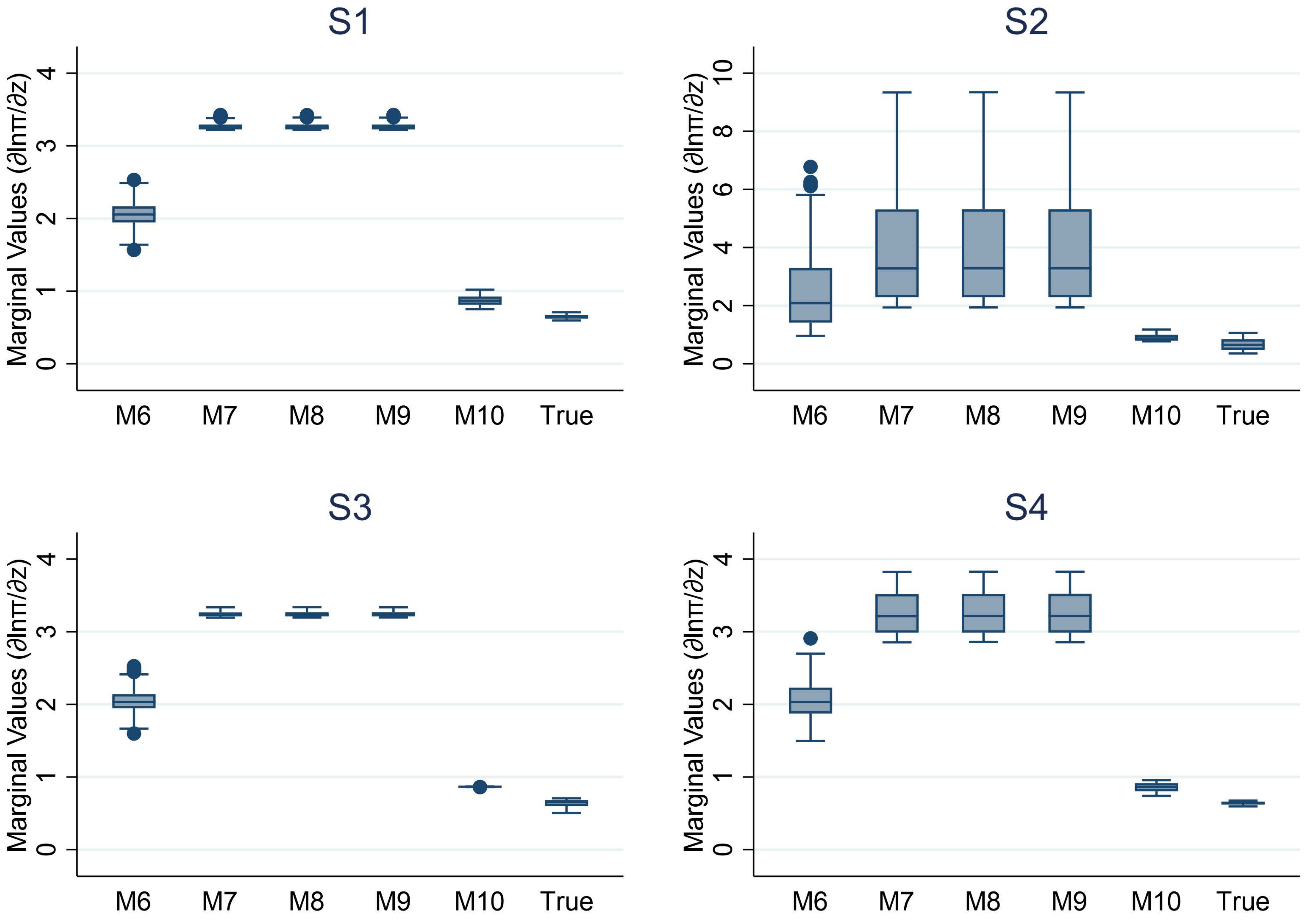
[19] Various entities (including firms, government agencies, and other organizations) may own and operate multiple ski areas. For simplicity, we broadly use the term “company” to refer to all such entities.

[20] Data on companies that own multiple ski areas were obtained from the National Ski Areas Association website: http://www.nsaa.org/press/industry-stats/industry-stats-pages/who-owns-which-mountain-resorts. Information on pass-sharing arrangements was obtained from the following sources: (1) https://zrankings.com/ski-resorts/season-passes; (2) https://www.coloradoski.com/gold-pass; (3) http://www.skiutah.com/passes/gold-and-silver-passes/goldpass-terms-of-use-benefits; and (4) http://www.thepowerpass.com. All website data were accessed via the Internet Archive (https://web.archive.org) to ensure alignment with the 2014-2015 season.

[21] While Table 3 indicates a slightly higher adjusted R^2 for the conventional hedonic Models 1 and 2 compared to our proposed Models 3 and 4 (under both linear and semi-log specifications), this does not necessarily imply their superiority. Similarly, AIC and BIC favor the conventional models. Using the Monte Carol simulation data from Section 3, our proposed models outperform the conventional hedonic price models in terms of the quality of benefit measures, but their adjusted R^2 values are lower, and their AIC and BIC values are higher than those of the conventional hedonic price models. This discrepancy highlights a crucial point: while measures of model fit are important, they should not be the sole criteria for model selection, especially in benefit estimation. Theoretical consistency, as embodied in our proposed approach, must also be a key consideration.

[22] Note that the empirical framework for imperfect competition within the hedonic method, as examined in this study, is currently limited to the commonly used linear and semi-log functional forms prevalent in nonmarket valuation. This limitation highlights the need for future research to extend the framework to accommodate a broader range of functional forms.


S1
S2
S3
S4
Marginal Values (∂π/∂z)
M1
M2
M3
M4
M5
True


S1
S2
S3
S4
Marginal Values (∂lnπ/∂z)
M6
M7
M8
M9
M10
True
0
1
2
3
4
6
8
10