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Valuing Vineyards: A Directional Distance Function Approach

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Abstract

We exploit the duality between the cost function and the directional distance function in value space to recover hedonic prices of product or asset characteristics. An application is offered for 96 Oregon vineyards located in the Willamette Valley of Oregon that sold between 1995 and 2007. Specifically, we recover hedonic prices for the number of high-, medium-, and low-quality vineyard acres and the number of nonvineyard acres sold in the parcel. Not surprisingly, higher-quality vineyard acres have a higher estimated hedonic price than medium- or low-quality acres, but as the number of high-quality acres increases, the hedonic price falls. (JEL Classification: D24, C61, Q10)

Keywords: Hedonic prices, directional distance function.

I. Introduction

Products or assets are often endowed with a set of characteristics. Although the characteristics of the product usually do not have explicit prices, changes in the bundle of characteristics cause the price of the product or asset to change. Sherwin Rosen (1974) built a structural model that assumed a spatial equilibrium in characteristics' space between producers and consumers, such that the hedonic price of a characteristic equaled both the consumer's marginal rate of substitution and the producer's marginal rate of transformation. Such a model allowed the implicit hedonic prices of product characteristics or attributes to be recovered by regressing product prices on characteristics. Over time, the hedonic price model has been widely adapted and refined, especially in the area of real estate, where observed house prices can be used to infer not only the values of the private characteristics of the house, such as the number of square feet, but also the values of the public good

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and neighborhood characteristics, such as environmental amenities and school quality. However, more than five decades of research has found that producers are not always efficient (Charnes, Cooper, and Rhodes, 1978; Farrell, 1957).

In this paper we outline a method that can be used to recover hedonic prices of product or asset characteristics even when producers are technically inefficient and produce inside their technological frontier. Our method uses the directional input distance function to represent the value/characteristics space of an asset. Directional distance functions were developed by Chambers, Chung, and Färe (1996, 1998) by adapting Luenberger's (1992, 1995) benefit function. Related to directional distance functions are Shephard (1953, 1970) distance functions, which are a special case of directional distance functions. The Shephard input and output distance functions scale inputs/outputs to an isoquant/production possibility frontier and can be used to infer the marginal rate of substitution between inputs or the marginal rate of transformation between outputs. Shephard input and output distance functions are most often estimated using a translog functional form. In contrast, Chambers (1998) shows that the quadratic function is more suitable for fitting directional distance functions. In addition, the quadratic form can handle data sets where one or more observations have one or more inputs/outputs that equal zero, whereas a translog function requires data to be transformed for use with observations with zeros for inputs or outputs.

Previous research by English, Grosskopf, Hayes, and Yaisawarng (1993) used Shephard output distance functions to estimate the shadow (hedonic) prices of unpriced outputs using the marginal rate of transformation and one observed output price. Färe, Grosskopf, Roland, and Weber (2009) used the Shephard input distance function to price the property right associated with owning a Norwegian license to farm salmon. Other research by Färe, Grosskopf, and Weber (2001) used directional distance functions to recover the shadow prices of the characteristics of sites overseen by the Missouri Department of Conservation. However, when the researcher has knowledge about the price of the bundle of characteristics but not the price of a single characteristic, the shadow pricing methods can allow recovery of the marginal rates of substitution or transformation but not the implicit equilibrium prices of the characteristics.

To circumvent the problem of unobservable characteristic prices, we exploit the duality between the cost function and the input characteristic distance function. Given the price of the bundle of characteristics and the quantities of the characteristics, we recover the implicit hedonic prices allowing for producer inefficiency. In the next section we present the theory used to recover the implicit hedonic prices of the characteristics of a product. Section III provides the functional form and estimation method. In Section IV we illustrate our proposed model by recovering hedonic prices of the characteristics of vineyards. The vineyards that we examine are located in the Willamette Valley of Oregon and were sold at various times between November 1995 and June 2007. In Section V we summarize our method and conclude.

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II. Method

We employ a production theoretical framework to value the characteristics of a good or an asset. Consider a good with characteristics $z=(z_1,\ldots,z_N)$. These characteristics determine the value of the good, $v \geqslant 0$. The value of the good depends on the price of the characteristics given by $p=(p_1,\ldots,p_N) \in R^N_+$. Thus, the value of the good is $v = p \cdot z = \sum_{n=1}^{N} p_n z_n$. The technology that transforms characteristics into value can be represented by the input correspondence

$$L(v) = \{z \in R^N_+ : \quad z \text{ generates value } v\}, \quad v \geqslant 0. \tag{1}$$

We assume that the input correspondence satisfies standard conditions like strong disposability of characteristics and value, no free lunch, and convexity (Färe and Primont 1995). These properties can be written as

$$\begin{aligned} &\text{If } z \in L(v), \text{ then for } z' \geqslant z, \quad z' \in L(v), \\ &\text{If } z \in L(v), \quad \text{then for } v' \leqslant v, \quad z \in L(v'), \\ &\text{If } v > 0, \text{ then } 0 \notin L(v), \\ &L(v) \text{ is convex for all } v \geqslant 0. \end{aligned} \tag{2}$$

Strong disposability of characteristics means that value does not decrease for goods with more of at least one characteristic and no less of the other characteristics. Strong disposability of value means that if characteristics z can produce a given value v, then those characteristics[1] can also produce less value. The property of no free lunch means that it is impossible to produce positive value out of zero characteristics.

The idea that characteristics create value can be seen as similar to the idea that labor and capital combine to create the gross domestic product (GDP). To move from the set representation of the technology to a functional representation, we use the directional input distance function of Chambers, Chung, and Färe (1996). The directional distance function is a special case of Luenberger's (1992, 1995) shortage function. Let the directional vector used to scale inputs to the input isoquant of $L(v)$ be represented by $g=(g_1,\ldots,g_N) \in R^N_+$. The directional input (characteristic) distance function takes the form

$$\vec{D}_i(v, z; g) = \max\{\beta : \quad z - \beta g \in L(v)\}. \tag{3}$$

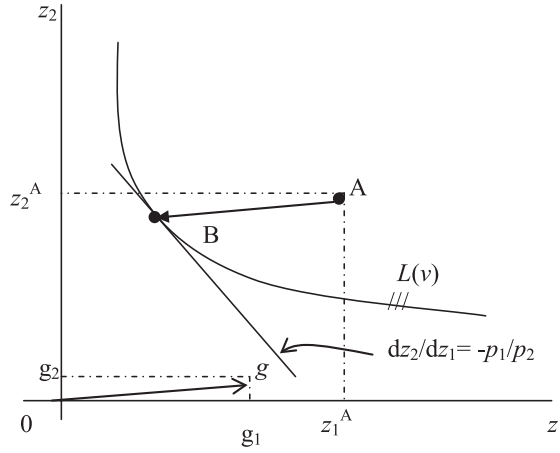
This distance function gives the maximum contraction in inputs or characteristics such that the remaining characteristics $(z-\beta g)$ can still generate value v. For $z \in L(v)$, we have $\vec{D}_i(z, v; g) \geqslant 0$, with $\vec{D}_i(z, v; g) = 0$ indicating that the producer is operating on the input characteristic g-isoquant. Figure 1 illustrates the input

[1] The input characteristic g-isoquant is $ISOQ(v)=\{z: \quad \text{for } \beta>0. \quad z-\beta g \notin L(v)\}$.

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Figure 1

The Value-Based Input Correspondence, $L(v)$



correspondence and directional input distance function given a directional vector $g=(g_1,\ g_2)$. The input correspondence that generates value, v, consists of all characteristics (z_1 and z_2) to the northeast of the curve. A producer (vineyard) has characteristics represented by point A. The directional input distance function for the producer is $\vec{D}_i(v, z; g) = \frac{AB}{0g}$.

The directional input distance function is a complete characterization of the input correspondence in that

$$\vec{D}_i(v, z; g) \geqslant 0 \quad \Leftrightarrow \quad z \in L(v). \tag{4}$$

In addition, the distance function is monotonic in inputs and value and satisfies the translation property:

$$\begin{aligned} &\text{If } z' \geqslant z \in L(v), \text{ then } \vec{D}_i(v, z; g) \leqslant \vec{D}_i(v, z'; g), \\ &\text{if } v' \leqslant v, \text{ then } \vec{D}_i(v', z; g) \geqslant \vec{D}_i(v, z; g), \text{ and} \\ &\text{for } \alpha \in \mathrm{R}_+, \quad \vec{D}_i(v, z + \alpha g) = \vec{D}_i(v, z; g) + \alpha. \end{aligned} \tag{5}$$

Dual to the input distance function is the cost function

$$C(v, p) = \min_z \left\{ \sum_{n=1}^{n} p_n z_n : \quad z \in L(v) \right\} = \min_z \left\{ \sum_{n=1}^{N} p_n z_n : \quad \vec{D}_i(v, z; g) \geqslant 0 \right\}. \tag{6}$$

Following Färe and Primont (1995) and assuming that p is the shadow (support) price vector for the characteristics, z, the duality between the cost function and the

directional input distance function can be summarized as

$$\begin{aligned} v = \sum_{n=1}^{N} p_n z_n = p \cdot z &= p \cdot z^*(v,p) + \vec{D}_i(v,z;g)pg. \\ &= C(v,p) + \vec{D}_i(v,z;g)pg. \end{aligned} \tag{7}$$

In words, Equation (7) says that actual costs equal the sum of minimum costs, $C(v, p)$, plus the extra cost of the firm not producing on the input isoquant for value v.

Let the gradient vector of the distance function with respect to z be represented by $\nabla_z \vec{D}_i(v,z;g) = \left(\frac{\partial \vec{D}_i(v,z;g)}{\partial z_1}, ..., \frac{\partial \vec{D}_i(v,z;g)}{\partial z_N}\right)$. Then, differentiating Equation (7) with respect to the characteristics yields the price vector

$$\begin{aligned} p = (p_1, ..., p_N) &= \nabla_z \vec{D}_i(v,z;g)pg \\ &= \left(\frac{\partial \vec{D}_i(v,z;g)}{\partial z_1}, ..., \frac{\partial \vec{D}_i(v,z;g)}{\partial z_N}\right) \times \sum_{n=1}^{N} p_n g_n. \end{aligned} \tag{8}$$

Multiplying Equation (8) by vector z yields

$$\begin{aligned} &p \cdot z = \nabla_z D_i(v,z)pg \cdot z \text{ or} \\ &\sum_{n=1}^{N} p_n z_n = \sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;g)}{\partial z_n} \times \left(\sum_{n=1}^{N} p_n g_n\right) \times z_n. \end{aligned} \tag{9}$$

Solving Equation (9) for pg yields

$$\begin{aligned} &pg = \frac{p \cdot z}{\nabla_z \vec{D}_i(v,z;g_z) \cdot z} = \frac{v}{\nabla_z \vec{D}_i(v,z;g_z) \cdot z} \text{ or} \\ &\sum_{n=1}^{N} p_n g_n = \frac{\sum_{n=1}^{N} p_n z_n}{\sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;g)}{\partial z_n} \times z_n} = \frac{v}{\sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;g)}{\partial z_n} \times z_n} \end{aligned} \tag{10}$$

Then, substituting Equation (10) into Equation (8) yields the hedonic price vector

$$\begin{aligned} p = (p_1, ..., p_n) &= \frac{\nabla_z \vec{D}_i(v,z;g) \cdot v}{\nabla_z \vec{D}_i(v,z;g) \cdot z} \\ &= \left(\frac{\frac{\partial \vec{D}_i(v,z;g)}{\partial z_1} \times v}{\sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;g)}{\partial z_n} \times z_n}, ..., \frac{\frac{\partial \vec{D}_i(v,z;g)}{\partial z_N} \times v}{\sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;g)}{\partial z_n} \times z_n}\right) \end{aligned} \tag{11}$$

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Thus, the price of each characteristic can be estimated given the directional input (characteristic) distance function and value using Equation (11). The methodology developed above is an analog to the hedonic price model of Färe, Grosskopf, Sheng, and Sickles (2012), who apply Shephard's (1953) input distance function rather than the directional input distance function. In parameterizing input distance functions different functional forms apply. The directional input distance function is modeled by the quadratic and the Shephard input distance function is modeled by the translog. See Färe, Martins-Filho, and Vardanyan (2010) for a discussion. Since we have zeros for certain inputs in our data, we use the quadratic directional input distance function. In addition, directional input distance functions are capable of modeling cases where some inputs are fixed, such as when regulations require minimum amounts of some inputs be used.

III. The Quadratic Directional Distance Function and Estimation Method

The translog functional form has been widely used to estimate Shephard input or output distance functions. The translog form serves as a second-order approximation to the unknown distance function, and its parameters can be restricted to satisfy the homogeneity property. However, when some firms use zero amounts of some inputs, the logarithmic transformation of the zero input is undefined, with researchers often adding an arbitrarily small positive value to the offending observation. For an example of this use, see Paul, Johnston, and Frengley (2000). Chambers (1998) suggests a quadratic form for the directional input distance function. The quadratic form serves as a second-order approximation to the unknown distance function and allows the researcher to impose the translation property on the parameters. Moreover, the quadratic specification allows the possibility of zero inputs, unlike the translog form. Since the data we employ on Oregon vineyards have some vineyards using zero amounts of some inputs, we price vineyard characteristics using the directional distance function estimated from a quadratic form.

We choose a directional vector equal to $g=(1, 1,\ldots,1)$ for all firms in our sample in order to avoid having to parameterize the directional vector, g, into our estimating equation. We assume there are $k=1,\ldots,K$ firms. The quadratic directional input distance function takes the form:

$$\vec{D}_i(v_k, z_k; 1) = \beta_0 + \sum_{n=1}^{N}\beta_n z_{nk} + \frac{1}{2}\sum_{n=1}^{N}\sum_{j=1}^{N}\beta_{nj} z_{nk} z_{jk} + \alpha_1 v_k + \frac{1}{2}\alpha_2 v_k^2 + \sum_{n=1}^{N}\delta_n z_{nk} v_k. \tag{12}$$

Symmetry of the second order terms implies that $\beta_{nj}=\beta_{jn}$, $n\neq j$. The distance function also satisfies the translation property in characteristics

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that yields restrictions on the quadratic form of $\sum_{n=1}^{N}\beta_n = 1, \quad \sum_{j=1}^{N}\beta_{nj} = 0, \quad n = 1, ..., N,$ and $\sum_{n=1}^{N}\delta_n = 0.$ To estimate Equation (12), we employ the deterministic method of Aigner and Chu (1968). The deterministic method has been used to estimate distance functions and recover shadow prices by English et al. (1993), Färe et al. (2001), and Färe, Grosskopf, Noh, and Weber (2005). The deterministic method chooses the parameters β_0, β_n, β_{nj}, α_1, α_2, and δ_{nm} so as to minimize the sum of the distances from each firm's observed inputs to the characteristic isoquant for each firm's value. The specific problem we estimate is

$$
\begin{aligned}
&\min \quad \sum_{k=1}^{K} \vec{D}_i(z_k, v_k; 1) \text{ subject to} \\
&i. \quad \beta_{nj} = \beta_{jn}, \quad n \neq j, \\
&ii. \quad \sum_{n=1}^{N}\beta_n = 1, \quad \sum_{j=1}^{N}\beta_{nj} = 0, \quad \sum_{n=1}^{N}\delta_n = 0, \\
&iii. \quad \frac{\partial \vec{D}_i(z_k, v_k; 1)}{\partial z_{kn}} = \beta_n + \sum_{j=1}^{N}\beta_{nj}z_{kj} + \delta_n v_k \geqslant 0, \quad n = 1, ..., N, \quad k = 1, ..., K, \\
&iv. \quad \frac{\partial \vec{D}_i(z_k, v_k; 1)}{\partial v_k} = \alpha_1 + \alpha_2 v_k + \sum_{n=1}^{N}\delta_n z_n \leqslant 0, \quad k = 1, ..., K, \quad \text{and} \\
&v. \quad \vec{D}_i(z_k, v_k; 1) \geqslant 0, \quad k = 1, ..., K.
\end{aligned}
\tag{13}
$$

The symmetry and translation restrictions are given by Equations (13*i*) and (13*ii*). The distance function is also positively monotonic in characteristics and negatively monotonic in value and these restrictions are given by Equations (13*iii*) and (13*iv*). That is, given value (v) an increase in any characteristic (z) will not increase efficiency, and, similarly, given characteristics (z) an increase in value (v) will not decrease inefficiency. Finally, Equation (13*v*) requires that the observation of characteristics and value for each of the K firms be feasible.

IV. Data and Estimates

To illustrate our method, we price the characteristics of 96 vineyards in Oregon's Willamette Valley that sold between November 1995 and June 2007. Numerous characteristics of the vineyard were recorded. The quality of the acres sold is classified into six segments and ranges from very high quality to low quality. Two other characteristics are the elevation of the acreage and the slope of the acreage. Elevation has nine categories corresponding to acreage with an elevation of less than 240 feet above sea level (the lowest elevation) to the highest elevation corresponding to acreage with an elevation of 500 feet or more above sea level. Slope is classified

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into six categories ranging from the number of acres with a slope between 0 to 4 degrees up to more than 12 degrees. Furthermore, the aspect of the acreage corresponding to whether it faces west, northwest, north, and so on is available for sixteen different aspect ranges of 22.5 degrees each. Some of the vineyards sold had a dwelling, and the square footage of the dwelling is available. Other vineyards had a barn or winery, and the square footage of these structures is also available. For vineyards with a winery, the cooperage in gallons is available. Soil type is classified into eight different categories corresponding to where the vineyard is located. The American Viticultural Areas (AVA) group the vineyard belongs to is also known and categorized into five different sub-AVAs. Cross, Plantinga, and Stavins (2011a, 2011b) examine vineyard sales prices as a function of the sub-AVA designation, holding other characteristics such as slope and elevation constant. The price premium is highest in the Dundee sub-AVA, followed by Yamhill sub-AVA, Chelahem sub-AVA, Eola Hills sub-AVA, and McMinnville sub-AVA.

The wealth of information on the characteristics of each vineyard is both a blessing and a curse, since only 96 vineyards are available to estimate the quadratic distance function. For instance, if one were to include ten characteristics in the distance function, there would be 74 parameters to estimate once the restrictions corresponding to symmetry and the translation property were imposed. In addition, the characteristics overlap and would result in some double counting. For instance, a hypothetical vineyard might comprise 60 acres, with 30 acres deemed high quality, 20 acres medium-high quality and 10 acres medium quality. Regarding elevation, 15 acres of the hypothetical vineyard are less than 250 feet above sea level and 45 acres are 250 to 300 feet above sea level. Regarding slope for our hypothetical vineyard, 35 acres have a slope of 2 to 4 degrees and 25 acres have a slope of 4 to 6 degrees. Furthermore, 10 acres face southeast and 50 acres face south. However, we do not know the number of high-quality acres with a slope between 2 and 4 degrees that have a southern exposure and an elevation of less than 250 feet. Thus, if each of the characteristics mentioned above is included in the distance function, there is some inevitable degree of double counting.

Faced with these difficulties, we choose a small subset of the characteristics to estimate the distance function and estimate hedonic prices. We focus on the total acreage that is sold. The total acreage is divided into four categories: acres not in the vineyard (z_1), high-quality vineyard acres (z_2), medium-quality vineyard acres (z_3), and low-quality vineyard acres (z_4). Since some, but not all of the properties sold included a dwelling, or a barn, or a winery, we subtract the appraised value of these assets from the sales price to obtain our valuation (v) of the acreage. The valuation of the acreage is deflated by the monthly Consumer Price Index (1982–84 = 100). In his book *Wine Wars*, wine economist Mike Veseth (2011) chronicles the various changes that have occurred in the global wine market. These changes include the opening of new markets in places like China, the relaxation of trade restrictions, changes in packaging ranging from screwtop bottles to cardboard box containers, and the growth in sales of low-price wine such as "Two Buck Chuck." Such changes

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Table 1
Descriptive Statistics

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Value (v)	369,106	267,623	80,770	1,656,210
Total acres	70.3	83.7	10	655
Vineyardpct	0.595	0.29	0.14	1
Nonvineyard acres (z_1)	17.5	16.0	0	87.4
High-quality vineyard acres (z_2)	7.8	13.7	0	69.3
Medium-quality vineyard acres (z_3)	41.8	73.2	0	655
Low-quality vineyard acres (z_4)	20.5	30.5	0	167
Proportion of vineyards in Chehalem AVA	0.21	0.41	0	1
Proportion of vineyards in Dundee AVA	0.25	0.44	0	1
Proportion of vineyards in Eola Hills AVA	0.35	0.48	0	1
Proportion of vineyards in McMinnville AVA	0.03	0.17	0	1
Proportion of vineyards in Yamhill AVA	0.16	0.36	0	1

have increased competition between producers but also increased demand. To account for these kinds of changes we include a time trend variable, t, ranging from 1 to 14 in the quadratic distance function. We also include indicator variables for the AVA area where the vineyard is located. There are five AVA areas: Chehalem (CH), Dundee (DU), Eola Hills (EA), McMinnville (M), and Yamhill (Y). To avoid an exact linear dependence among the five AVAs, we drop the Yamhill AVA variable in the estimation. The AVA coefficients are reported as ϕ_{ava}, $ava = 1,\ldots,4$. The time trend (γ) and AVA designation will shift the intercept (β_0) for each vineyard.

Descriptive statistics are found in Table 1. The 96 vineyards ranged in value from \$80,770 to \$1,656,210 with an average of \$369,106 in 1982–84 constant dollars net of the appraised value of any dwelling, barn, or winery located on the property. The average are was 70.3 acres and ranged from 10 to 655 acres, with an average of 59.5% under cultivation. The average property had 17.5 nonvineyard acres (z_1) , 7.8 high-quality vineyard acres (z_2), 41.8 medium-quality vineyard acres (z_3), and 20.5 low-quality vineyard acres (z_4). Of the 96 vineyards, 21% were located in the Chehalem AVA, 25% in the Dundee AVA, 35% in the Eola Hills AVA, 3% in the McMinnville AVA, and 16% in the Yamhill AVA.

Parameter estimates of the quadratic distance function are reported in Table 2, and estimates of efficiency are reported in Table 3. Fifteen vineyards produced on the efficient frontier with $\vec{D}_i(v, z; 1) = 0$. The mean value of the directional distance function, $\overline{\vec{D}_i(v, z; 1)} = 2.5$, indicates that on average, a vineyard could generate the same level of value using 2.5 fewer acres of each type. The time trend coefficient, $\gamma = 0.092$, indicates that, with each passing year, the Willamette Valley vineyards can generate the same level of value with approximately 0.092 fewer acres of each of the four types. Relative to vineyards in Yamhill AVA, vineyards in the AVAs of Chelahem (CH), Dundee (D), Eola Hills (EA), and McMinnville (M) are more inefficient. That is, these vineyards could generate the same level of value using fewer inputs than a vineyard in the Yamhill AVA. In contrast, Cross, Plantinga, and

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Table 2
Parameter Estimates of Quadratic Directional Distance Function

Coefficient	*Variable*[1]	*Estimate*
β_0	Constant	0.201411
β_1	z_1	−0.00339
β_2	z_2	−8E–06
β_3	z_3	0.006486
$\beta_4 = 1 - \beta_1 - \beta_2 - \beta_3$	z_4	0.97509
β_{11}	z_1^2	0.016146
$\beta_{12} = \beta_{21}$	$z_1 z_2$	0.002278
$\beta_{13} = \beta_{31}$	$z_1 z_3$	−0.00042
$\beta_{14} = \beta_{41}$	$z_1 z_4$	0.000214
β_{22}	z_2^2	0.000101
$\beta_{23} = \beta_{32}$	$z_2 z_3$	0.0001
$\beta_{24} = \beta_{42}$	$z_2 z_4$	−0.00019
β_{33}	z_3^2	0.00002
$\beta_{34} = \beta_{43}$	$z_3 z_4$	−4.7E–05
β_{44}	z_4^2	−7.1E–05
α_1	v	−0.00005
α_2	v^2	−3E–06
δ_1	$v z_1$	0.000046
δ_2	$v z_2$	−8.3E–05
δ_3	$v z_3$	0.000018
$\delta_4 = -\delta_1 - \delta_2 - \delta_3$	$v z_4$	0.000018
ϕ_1	CH-AVA	−0.15431
ϕ_2	DU-AVA	−0.10132
ϕ_3	EA-AVA	−0.52091
ϕ_4	M-AVA	−0.54213
γ	Time	0.092134

1. v = value of vineyard, z_1 = nonvineyard acres, z_2 = high-quality vineyard acres, z_3 = medium-quality vineyard acres, z_4 = low-quality vineyard acres, CH = Chelaham AVA, DU = Dundee AVA, EA = Eola Hills AVA, and M = McMinnville AVA.

Table 3
Estimates of Efficiency and Hedonic Prices

Variable	*Mean*	*Std. Dev.*	*Min.*	*Max*
$\vec{D}_i(v, z; 1)$	2.5	4.5	0	23
p_1(nonvineyard acres)	5,566	5,775	0	33,330
p_2(high-quality vineyard acres)	279,358	257,895	0	1,430,320
p_3(medium-quality vineyard acres)	5,896	5,440	590	31,770
p_4(low-quality vineyard acres)	2,186	1,912	0	11,110

Note: Prices are deflated relative to a base year of 1982–1984.

Stavins (2011a, 2011b) found an ascending price premium for vineyards in the McMinnville, Eola Hills, Chelahem, Yamhill, and Dundee sub-AVAs. One possible reason for the different results arises from differences in method. We used a deterministic approach and disaggregated total acres into nonvineyard acres and the quantities of acres in the vineyard that were of high, medium, and low quality,

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whereas Cross, Plantinga, and Stavins used a regression approach and included all vineyard acres as an explanatory variable and then used the shares of acreage with the best and medium soil qualities as additional explanatory variables.

For the quadratic distance function given in Equation (12) the hedonic prices are calculated from Equation (11) as

$$p_n = \frac{\frac{\partial \vec{D}_i(v,z;1)}{\partial z_n} \times v}{\sum_{n=1}^{N} \frac{\partial \vec{D}_i(v,z;1)}{\partial z_n} \times z_n} = \frac{\left(\beta_n + \sum_{j=1}^{N} \beta_{nj} z_j + \delta_n v\right) \times v}{\sum_{n=1}^{N} \left(\beta_n + \sum_{j=1}^{N} \beta_{nj} z_j + \delta_n v\right) \times z_n}. \tag{14}$$

We use Equation (14) to calculate the hedonic prices for vineyards that had positive quantities of the characteristics. Each vineyard has different characteristics, z, and value, v, resulting in different hedonic prices for each characteristic. Table 3 reports the means and standard deviations for the hedonic prices for each of the four characteristics for the 96 vineyards. The standard deviations should not be interpreted as standard errors since our estimation method using Equation (13) is deterministic, not stochastic. Instead, the standard deviation of the hedonic price of each characteristic is just a descriptive statistic measuring dispersion. An additional nonvineyard acre is priced at \$5,566, a high-quality vineyard acre is priced at \$279,358, a medium-quality vineyard acre is priced at \$5,896, and a low-quality vineyard acre is priced at \$2,186. We further investigate the very high average price of a high-quality vineyard acre. Sixty of the 96 vineyards had zero high-quality acres in their vineyard. For the 60 vineyards without any high-quality acres, the hedonic price of the first acre averaged \$403,447. The 36 vineyards with positive high quality acres averaged 7.5 high-quality acres, ranging from a mere half an acre to 27 acres. The average hedonic price per high-quality acre for those 36 vineyards equaled \$83,817, ranging from \$22,680 to \$305,650. Referring again to Figure 1, suppose that high-quality acres are represented by z_2 on the y-axis. Then, an explanation of the relatively high average price per high-quality acre is that almost two-thirds of the vineyards in our sample have no high-quality acres and the directional distance function is projecting them to a relatively flat portion of the input characteristic isoquant, resulting in a very high hedonic price.

We use the parameter estimates found in Table 2 and the hedonic price equation in Equation (14) to simulate hedonic prices for high-quality vineyard acres, holding the other three input characteristics constant. We consider a hypothetical vineyard with z_1, z_3, z_4, and v equal to the average for those variables given in Table 1, and we allow the number of high-quality vineyard acres (z_2) to range from 0 to 80.

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Table 4
Simulation of Hedonic Prices of High-Quality Vineyard Acres for a Hypothetical Vineyard

	1	*2*	*3*	*4*	*5*
High-quality acres (z_2)	*Hedonic Price of* z_2	*Hedonic Price of* z_2	*Hedonic Price of* z_2	*Hedonic Price of* z_2	*Hedonic Price of* z_2
0	245,130	303,374	210,925	135,238	208,927
1	147,062	205,176	133,846	98,796	133,283
2	105,039	155,004	98,025	77,825	97,854
3	81,695	124,548	77,329	64,198	77,305
4	66,840	104,095	63,849	54,632	63,889
5	56,556	89,411	54,371	47,547	54,441
6	49,015	78,358	47,343	42,089	47,427
7	43,248	69,738	41,924	37,755	42,014
8	38,696	62,826	37,618	34,230	37,710
9	35,010	57,160	34,114	31,307	34,206
10	31,966	52,432	31,207	28,844	31,298
15	22,279	37,091	21,884	20,701	21,962
20	17,097	28,696	16,850	16,143	16,916
25	13,871	23,399	13,699	13,230	13,755
30	11,670	19,753	11,540	11,208	11,590
35	10,071	17,090	9,970	9,722	10,014
40	8,858	15,060	8,775	8,584	8,815
45	7,905	13,461	7,836	7,684	7,872
50	7,138	12,169	7,079	6,955	7,112
55	6,506	11,103	6,455	6,353	6,485
60	5,977	10,209	5,932	5,846	5,960
65	5,527	9,448	5,488	5,414	5,514
70	5,141	8,792	5,105	5,042	5,130
75	4,805	8,222	4,773	4,718	4,796
80	4,510	7,721	4,481	4,432	4,502

Note: z_1 = nonvineyard acres, z_3 = medium-quality vineyard acre, z_4 = low-quality vineyard acre, and v = vineyard value.
1. $z_1 = 17.5$, $z_3 = 41.8$, $z_4 = 20.5$, and $v = \$369{,}106$.
2. $z_1 = 17.5$, $z_3 = 41.8$, $z_4 = 20.5$, and $v = \$636{,}623$.
3. $z_1 = 33.5$, $z_3 = 41.8$, $z_4 = 20.5$, and $v = \$369106$.
4. $z_1 = 17.5$, $z_3 = 115$, $z_4 = 20.5$, and $v = \$369106$.
5. $z_1 = 17.5$, $z_3 = 41.8$, $z_4 = 51$, and $v = \$369{,}106$.

The hedonic prices of the high-quality acres for the hypothetical vineyard are reported in Table 4 in column 1. The hedonic price falls rapidly from \$147,062 for the first acre to \$105,039 for second acre, to \$31,966 for the tenth acre, and \$4510 for the eightieth acre. The hedonic prices of high quality acres are dependent on the quantities of the other three characteristics and value. We increase each characteristic and value by one standard deviation, holding the other variables constant and report the new set of hedonic prices for high-quality acres in columns 2 to 5 of Table 4. Increasing value (v) by one standard deviation ($v = \$636{,}729$) and holding z_1, z_3, and z_4 constant at their mean increases the hedonic prices of high-quality acres (column 2). Increasing nonvineyard acres (z_1) by one standard deviation ($z_2 = 33.5$), holding v, z_3 and z_4 constant at their mean, lowers the hedonic price of high-quality acres (column 3). Increasing medium-quality acres (z_3) by one

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standard deviation ($z_3 = 115$), holding v, z_1 and z_4 constant, lowers the hedonic price of high-quality acres (column 4). Finally, increasing low-quality acres (z_4) by one standard deviation ($z_4 = 51$), holding z_1, z_3, and v at their means, lowers the hedonic price of high-quality acres (column 5).

Our simulation illustrates the usefulness of our approach in calculating hedonic prices. In general, the hedonic price of a characteristic should depend on the amount of the characteristic along with the amounts of other characteristics and value. Models that assign a single hedonic price to a characteristic fail to account for the possibility that characteristics can substitute for one another. Furthermore, our method accounts for the possibility that when value changes, the hedonic prices might change by more or less than that change in value. For instance, the increase in value from \$369,106 to \$636,729 corresponds to a 72.5% increase, but for a vineyard with only 1 high-quality acre the hedonic price increased by only 23.8%, while it increased by 71% for a vineyard with 80 high-quality acres (see columns 1 and 2 of Table 4).

V. Conclusions

In this paper, we proposed a method of estimating the hedonic prices of characteristics that is theoretically grounded in production theory and accounts for firm inefficiency. Our method exploits the duality between the directional input distance function and the cost function. Unlike shadow pricing models, which require knowledge of the price of at least one input and the marginal rate of substitution between inputs to recover the support price of an unpriced input, our hedonic method recovers the hedonic prices of all unpriced input characteristics, given a differentiable directional distance function and the value (cost) of the bundle of characteristics. We used our method to estimate hedonic prices for four characteristics of 96 vineyards in the Willamette Valley of Oregon that sold between November 1995 and June 2007. The characteristics include the number of acres of high, medium, and low quality in the vineyard as well as the number of nonvineyard acres that are included in the sold parcel. Information on other characteristics such as slope, elevation, and number of acres facing south, southwest, west, and so on are available, but the small number of parcels sold relative to the number of parameters that would have to be estimated preclude us from including these other characteristics. An anonymous referee suggested that principal components analysis might be one way to address this problem, and we leave that suggestion for future work.

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