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Estimating supply functions for wine attributes: a two-stage hedonic approach

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Abstract

A vast body of literature exists on estimating hedonic price functions which relate the price of wine to its attributes. Some studies have employed producer specific variables such as quantity sold and producer reputation in hedonic functions to potentially capture supply influences on prices. This paper recognizes that the original Rosen (1974) hedonic theoretic framework excludes producer specific variables from the hedonic price function and justifies their inclusion only for second-stage attribute supply estimation. We use the two-stage Rosen approach employing data from multi-markets for the same wines to identify supply functions. The application to Australian produced wines demonstrates the importance of a wine's quality and age as attributes in inverse supply functions. Counter to expectations a direct relation between producer size and marginal attribute costs is estimated which appears to be due to the method employed rather than the peculiarities of the data.

Keywords: attribute supply, wine prices, Australian wines

JEL codes: C21, Q11

1. Introduction

There exists significant interest in modelling the determinants of price variations for differentiated products. The hedonic approach which assumes prices are determined by the attributes or characteristics of products is typically employed, recent empirical examples of the approach include Fedderke and Li (2020) and Oczkowski (2020) for artworks. A substantial body of literature has also developed over 25 years which uses the hedonic approach to estimate the relation between the price of wine and its attributes. Attributes typically include a sensory rating of the wine's quality, the impact of weather, the wine's vintage, grape variety and region. Over 100 papers estimating hedonic wine price functions have been identified by Outreville and Le Fur (2020). In part, the vast array of studies over time and across many countries is driven by the highly differentiated nature of wine products making wine a prime candidate for hedonic price function estimation.

The hedonic wine price literature typically cites the Rosen (1974) framework as its theoretical basis. Rosen's (1974) perfect competition framework suggests consumers and producers interact to demand and supply a product with various attributes. This interaction results in a market determined hedonic price function which is a function of attributes alone. The presence of specific attributes is motivated by their inclusion in the representative consumer's utility function and producer's cost function. The price function results from an envelope of various consumer bid and producer offer functions, which however, cannot uncover individual consumer or producer specific features. Most estimated hedonic wine functions recognize the need to use only wine attributes. However, some studies have included producer specific variables in the hedonic price function to capture supply influences on prices. For example, Outreville and Le Fur (2020) list 17 papers which employ quantity sold and/or producer size in hedonic price functions.

This paper recognizes that the inclusion of producer specific variables in the hedonic price function is inconsistent with the Rosen (1974) framework. To overcome this deficiency, Rosen's (1974) two-stage approach should be employed to accurately estimate the supply of wine attributes which includes producer specific variables. The first stage consists of estimating a standard hedonic price function based on attributes only. Then estimated marginal attribute prices are used in a second stage which includes producer specific variables. To identify the inverse supply function, price data from multi-markets of different consumers is used for similar wines.

This paper presents what appears to be the first application of Rosen's (1974) two-stage approach for estimating wine attribute supply functions. The two-stage approach is applied to Australian produced wines sold in Australia and some of its major international markets. The focus of producer specific variables rests with producer size, experience, reputation and the potential influence of wine conglomerates. The application is important as it will help clarify the relation between producer size and attribute prices. This relation has gained considerable attention in the literature and arguments around the potential effects of economies scale in production are used to rationalize the typically estimated inverse relation between quantity sold and price in hedonic price functions. In contrast, this paper employs the more theoretically consistent two-stage approach to identify the relation between producer size and marginal attribute prices. Unexpectedly, results point to a direct relation between producer size and marginal attribute prices which appears to be principally due to the different method employed rather than the peculiarities of the data set.

Given the scarcity attribute supply estimation applications in the general economics literature and that this paper appears to provide the first attribute supply estimates for wine, we initially provide an overview of hedonic price theory and estimation in the next section. In section 3 hedonic wine price models in general are discussed. Section 4 outlines the data and specifies the hedonic wine functions to be estimated. The results are presented in section 5 with a discussion and conclusion provided in section 6.

2. Hedonic Price Theory and Estimation

Rosen (1974) assumes a good can be characterized by n different attributes z_i whose price is described by a hedonic price function $p(z) = p(z_1, z_2, \ldots z_n)$. The partial derivative of p(z) is termed the marginal implicit price p_i $(=\partial p(z)/\partial z_i)$. Rosen (1974) assumes perfect competition and prices p(z) are determined by the market.

Given the market determined p(z), consumers are assumed to choose levels for attributes by maximising utility (u) subject to an income (y) constraint. This results in a bid (or value) function $\theta(z; u, y, \alpha)$, where α specifies individual consumer specific tastes. The bid function specifies the maximum price they are willing to pay for an attribute z at a fixed level of utility and income given their tastes.

Symmetrically, given p(z), producers are assumed to choose the number of units (M) of the good and levels of z to produce by maximising profits (π).

$$\underset{m,z}{Max}\ \pi = M\,p(z) - C(M, z_1, z_2, \ldots z_n) \qquad (1)$$

where C(.) represents the total cost function gained after minimising factor costs given its production technology. It is assumed that C is convex with $C_M > 0$, $C_{z_i} > 0$, and $C_{z_i z_i} > 0$.

The first order conditions for maximizing (1) imply:

$$p_i(z) = C_{z_i}(M, z_1, \ldots z_n)/M \qquad i = 1, \ldots n \qquad (2)$$

$$p(z) = C_M(M, z_1, \dots . z_n) \quad (3)$$

This program results in an offer function $\phi(z; \pi, \beta)$, where β specifies differences among producers in terms of factor prices and technology. The offer function describes the minimum price that producers are willing to receive for attributes z at the fixed level of profit for the optimally chosen output level. Using eqn (2), profit maximization results in ϕ_{z_i} (= $\partial\phi/\partial z_i$) = C_{z_i}/M, that is, the marginal offer function equals the marginal cost per unit of producing the attribute. The optimization program assumes $\phi_{z_i} > 0$ and $\phi_{z_i z_i} > 0$.

In equilibrium, tangents among the bid and offer functions 'kiss' at various levels of z to trace out p(z). The marginal bid θ_{z_i} (= $\partial\theta/\partial z_i$), marginal offer ϕ_{z_i} and marginal price p_i are equal in equilibrium for attribute z_i. The p(z) function is just a function of z and does not reveal any information about y, α and β as it is a result of a joint envelope of the bid and offer functions.

To estimate marginal bid and marginal offer functions a two stage approach was initially recommended by Rosen (1974). In the first stage estimate the hedonic price function in eqn (4):

$$p(z) = H(z_1, z_2, \dots z_n) \quad (4)$$

and calculate the respective marginal hedonic prices

$$\widehat{p_i} = \partial \widehat{H}(z)/\partial z_i \qquad i = 1,2,..n \quad (5)$$

Substitute (5) into the empirical counterpart marginal bid and marginal offer functions:

$$\widehat{p_i} = F_i(z_1, z_2, \dots z_n, Y_1) \qquad i = 1,2,..n \quad (6)$$

$$\widehat{p_i} = G_i(z_1, z_2, \dots z_n, Y_2) \qquad i = 1,2,..n \quad (7)$$

Eqn (6) are the empirical marginal bid functions where Y_1, captures the demand shifters y (income) and α (taste differences). While eqn (7) are the empirical marginal offer (inverse supply) functions where Y_2, captures the supply shifters β (factor price and technology differences).[1]

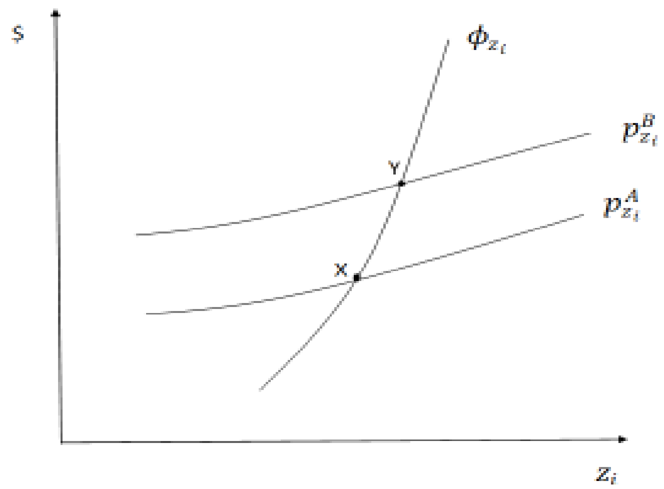
Brown and Rosen (1982) point out a fundamental identification problem in estimating (6) and (7) from single market data as effectively eqn (4) contains the same information as (6) and (7) unless further restrictions are imposed. Two methods have been employed to overcome this identification problem: 1) impose restrictions on the functional forms employed (e.g., Quigley 1982); or 2) employ data from multiple markets in estimating (6) and (7) (Brown and Rosen 1982). In the latter case eqn (4) is estimated separately for each market and then using marginal prices from (5), data from all markets is combined to estimate a single marginal bid (6) and marginal offer (7) function for the individual attributes. The use of multiple markets data to estimate

[1] In equilibrium, eqn (7) can be referred to as either the marginal offer, marginal cost or inverse supply function for the attribute. These terms are used interchangeably for eqn (7) throughout the paper.

marginal bid or inverse demand functions has frequently been employed for housing markets, see for example, Palmquist (1984), Bartik (1987), Zabel and Kiel (2000) and Jun (2019).

We focus on marginal offer or inverse supply estimation using a multi-market data approach. Unlike demand studies, it appears only a few studies have explicitly estimated marginal offer functions employing the multi-market data, examples include: Witte, Sumka and Erekson (1979), Kinzy (1982) and Coulson, Dong and Sing (2018) for housing markets, Pardew, Shane and Yanagida (1986) for agricultural land prices, and Thomas (1993) for the motor carrier industry. Effectively, the task is to identify separate groups of consumers who have different tastes and preferences for similar goods.[2] If the marginal prices across these separate markets are different then sufficient data variability will exist to trace out the marginal offer or inverse supply function. The intuition is illustrated in figure 1 where two separate consumer markets (A and B) exist for the same good. Assume the marginal price function for attribute z_i is upward sloping and exists for two separate markets depicted by the curves $p_{z_i}^A$ and $p_{z_i}^B$. An upward sloping marginal offer curve is also depicted by the ϕ_{z_i}curve. If only one market A existed, the marginal offer curve cannot be identified as only one point (X) on it exists. However, assuming that the model types are similar across the two markets A and B, two points (X and Y) can be identified to trace out the marginal offer curve.

Figure 1. Multi-Market Marginal Offer Function



[2] This contrasts to the standard bid function estimation case in housing markets. For housing markets, it is typically assumed that consumer preferences are similar across markets but supply differences in terms of housing types, allow for the identification of the inverse demand function.

Given our focus on inverse supply estimation it is useful to discuss some of the properties of eqn (7). There is an expectation the own attribute price marginal estimate is positive $\phi_{z_i z_i} = \partial G_i / \partial z_i > 0$, this flows from the convexity assumption of the total cost function and suggests that at the profit maximising position producers operate on a positively sloped marginal cost curve for the attribute, see for example Palmquist (1989, p.25). Theoretically, the cross marginal attribute estimates are difficult to sign *a priori*. One possibility is cross attribute effects may also reflect the increased marginal costs of the production of an attribute as the use of other attributes are increased and hence $\phi_{z_i z_j} = \partial G_i / \partial z_j > 0$. For example, Witte, Sumka and Erekson (1979, p1168), suggest their finding that an increase in dwelling size produces an increase in the marginal offer price for dwelling quality, simply reflects the greater costs required to produce more dwelling quality as the size of a dwelling increases. Similarly, Thomas (1993, p668) for the motor carrier industry, suggests the estimated higher marginal offer price of service intensity as a result of higher performance, reflects that higher service intensity becomes more costly as performance increases. For non-attribute related regressors contained in Y_2, the nature of the supply shifter will determine its impact on marginal offer prices.

It will prove instructive to comment on the role that M (the number of units of the good produced) plays in previously estimated marginal offer functions. The interpretation of estimates for the impact of M on ϕ_{z_i} typically relates to a discussion of economies of scale, which may or may not be consistent with the original Rosen (1974) producer framework. For example, Witte, Sumka and Erekson (1979) estimate a negative impact for the number of units owned by a landlord for both dwelling quality and dwelling size marginal prices and suggest this implies economies of scale in the production of houses and quantity discounting. While, Thomas (1993) finds that quantity is largely unimportant and statistically insignificant in various marginal offer models for the motor carrier industry and concludes this implies firms are producing quality in the constant returns of scale range. In general, these interpretations effectively view M as a supply shifter identifying differences among firms in terms of their scale of operation.

3. Hedonic Wine Price Models

In the hedonic wine pricing literature it appears most studies have only estimated the first stage hedonic price function, using eqn (4). Outreville and Le Fur (2020) provide a classification and summary description of most previously estimated hedonic wine price models and point to a vast array of variables employed in first stage hedonic wine price functions which include: weather/climate, soil/terroir, grape region of origin/appellation, grape varieties, public information (including, label information and expert ratings), and the wine's age (vintage). Outreville and Le Fur (2020) further classify some studies which argue the supply of wine impacts price through the use of variables such producer size or quantity produced in hedonic price functions. An important issue is some of these previous studies have not made an explicit distinction between z (attributes) and Y_2 (supply shifters) and have included both variable types in hedonic price functions.

The Rosen (1974) framework suggests, for a given distribution of consumers (Y_1) and producers (Y_2), attributes (z) consist of variables which influence the utility of consumers and the production costs of producers, in the sense bid and offer functions kiss to determine the market hedonic price function. For example, consider an improvement in a wine's quality (however measured), this will increase a consumer's utility (increasing their bid price) but will also increase the costs of producing the wine for the producer (increasing their offer price). As a consequence the kiss between bid and offer functions (across Y_1 and Y_2) occur at higher levels of wine quality resulting in a positive marginal price for wine quality. This occurs not because of changes in variation among consumers (Y_1) and producers (Y_2) but because of how wine quality enters the typical consumer's utility function and producer's cost function. To this extent most variables employed in hedonic wine functions can be justified as attributes as they influence the utility and costs of the representative consumer and producer.

If the Rosen framework is adopted however, the quantity of the wine produced and producer size are producer specific and as such should be excluded from eqn (4) and only employed as Y_2 in estimating a marginal offer function. Outreville and Le Fur (2020) list 11 papers which employ the quantity of the wine produced and six studies which employ some measure of producer size in hedonic price functions. In nearly every study a negative relation between quantity (or producer size) and price is estimated and arguments about economies of scale are offered as interpretations.

A number of counter arguments, however, have been offered for the inclusion of producer size in eqn (4). For example, Oczkowski (2016a) argues that the production from small producers may have some 'rarity, scarcity, collectability, exclusivity and cult status' (p45) consumer desirable value and hence producer size is included in the price function because it appears in the typical consumer's utility function. Alternatively, the perfect competition assumption is said to be violated and Rosen's framework is abandoned as some production levels for individual producers are too large and some aspects of imperfect competition price making occurs. Both these arguments are typically not supported by any explicit theoretical development and are offered as ad-hoc justifications for including quantity and producer size in hedonic price functions.

The criticism of the use of producer specific variables directly in hedonic price functions also applies to the use of producer fixed effects in price models as they control for differences among producers which are supply shifters rather than attributes. A similar criticism could possibly be made to hedonic price functions where consumer specific characteristics are included in first stage models. However, models which employ different consumer characteristics to identify different market segments for wine (Caracciolo and Furno 2020), may be theoretically justified using a modified Rosen theoretical framework for different market segments (Baudry and Maslianskaia-Pautrel 2016).

4. Data and the Hedonic Wine Price Function

We consider Australian produced wine sold in different countries as the multi-market data set. Effectively, the same product is sold in a variety of countries and it is postulated consumers across these countries have different tastes and preferences. In total value terms, Australia is the fourth largest exporter of wines in the world (OIV 2019). In terms of total export value of bottled wines, the major export markets Australia serves are China (including Hong Kong and Macau), United States and United Kingdom (Wine Australia 2019a).

The database employed to collect information on the main characteristics of wines is James Halliday's *Australian Wine Companion* (AWC) (https://www.winecompanion.com.au/). The AWC provides the most authoritative and comprehensive assessment of Australian wines and has been extensively used in hedonic price studies, including, Schamel and Anderson (2003) and Oczkowski and Pawsey (2019). Using the AWC as the sampling frame, data on market prices is accessed from wine searcher (https://www.wine-searcher.com/). Average retail market prices were collected for Australian produced wines available for sale during January 2020 from wine merchants located and selling to consumers in four countries: Australia, Hong Kong, United States and United Kingdom.[3] To capture the notion of different consumers purchasing similar Australian wines, wines sold in Australia are only included in the analysis if they are available in at least one other country. All non-Australian prices are converted to $AUD using the average of daily exchange rates for the month of January 2020 (https://rba.gov.au/).

For the hedonic price function we employ a standard specification:

$$\text{Price} = f(\text{quality rating, vintage years, wine variety, wine region}) \qquad (8)$$

[3] The data on prices is collected before any noticeable impact of COVID-19 on markets. In wine searcher, only a few merchants are located in mainland China, however, a sufficiently large number exist in Hong Kong.

where, *Price* is the average market retail price measured in \$AUD[4]; *Quality Rating* is the expert rating score out of 100 from the AWC; *Vintage Years* is the difference between 2019 and the year of grape harvest; *Wine Variety* is a series of dummy variables reflecting the variety employed; and *Wine Region* is a series of dummy variables reflecting the region from where the grapes are sourced.

The use of expert quality ratings is a dominant feature of many hedonic wine studies. Oczkowski and Doucouliagos (2015) have identified over forty studies which have employed expert ratings to explain price. Expert ratings might be viewed as an average measure of consumer preferences (Costanigro, McCluskey and Goemans 2010) or as providing opinion leadership for consumers. Both arguments imply that ratings potentially reflect consumer preferences for higher quality wines. Expert ratings may also capture the higher costs in producing better quality wines, such as the use of better quality grapes or new oak barrels for maturation. Further, in the Australian context Oczkowski (2016b) demonstrates how expert ratings may also capture the indirect effects of annual weather variations on prices.

Vintage years captures any consumer preferences for aged wines and the additional costs of maturation and storage for older wines. To control the sample design, we limited analysis to five major single varieties where at least ten wines are available in each of the four designated countries. The identification of wine regions was based on Australian geographical indications (GIs) and dummy variables defined if at least ten sampled wines in each country existed. For wines not classified to a main region, two variables were employed, wines sourced from a cool climate (long term growing degree days (GDD) less than 1668) and those from a warm climate (GDD = 1668 or greater), see Hall and Jones (2010). Both wine variety and region capture consumer preference and cost of production features for these wine characteristics.[5]

Summary sample statistics for the entre sample of wines from all four countries are provided in table 1. A wide variety of different priced[6] and quality wines exist in the sample. Prices range from less than \$9 to over \$350, the mean price of \$52 indicates that mainly premium wines dominate the sample. The median price of \$39 indicates a highly skewed distribution. Quality scores vary accordingly from a low of 84 to a high of 99 and average 93.

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[4] The average market price is the price paid by consumers and includes sales tax. An alternative is to use of prices which to exclude sales taxes, tariffs, transport costs and other duties to produce international comparable prices (Cardebat et al., 2017). In our case similar empirical modelling results are gained from both the use of retail prices and prices which exclude taxes and other costs. Results based on retail prices are preferred and presented given these prices reflect what consumers actually pay in the various countries.

[5] It is important to note that individual producer specific variables are excluded from eqn (8) as suggested by Rosen (1974) framework.

[6] To avoid the impact of any outliers, wines with prices exceeding \$500 were omitted from the analysis.

Table 1. Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum
Price ($AUD)	52.06	39.90	8.80	350.9
ln (Price)	3.753	0.598	2.175	5.861
Quality Rating	93.17	3.114	84	99
Vintage Years	2.240	0.966	1	7
$(\text{Quality Rating})^2$	8691	573.2	7056	9801
$(\text{Vintage Years})^2$	5.950	5.876	1	49
Quality * Vintage Years	209.1	91.90	84	679
Varieties				
Cabernet Sauvignon	0.169	0.375	0	1
Chardonnay	0.204	0.403	0	1
Pinot Noir	0.146	0.353	0	1
Riesling	0.097	0.296	0	1
Shiraz	0.385	0.487	0	1
Regions				
Barossa Valley	0.161	0.368	0	1
Clare Valley	0.082	0.274	0	1
Cool Climate	0.312	0.464	0	1
Margaret River	0.140	0.347	0	1
McLaren Vale	0.137	0.344	0	1
Warm Climate	0.106	0.308	0	1
Yarra Valley	0.062	0.241	0	1
Producer Variables				
Size (1000 cases)				
0 - 19.9	0.355	0.479	0	1
20 - 49.9	0.250	0.433	0	1
50 - 99.9	0.154	0.361	0	1
100-499.9	0.157	0.363	0	1
500 or over	0.084	0.278	0	1
Established (Year)				
After 2000	0.243	0.430	0	1
2000 or Before	0.757	0.429	0	1
Conglomerates				
Accolade Wines	0.020	0.140	0	1
Pernod Ricard	0.019	0.138	0	1
Treasury Wine Estates	0.043	0.203	0	1
Non-conglomerate wineries	0.918	0.275	0	1
Producer Reputation Rating	5.307	0.405	3	5.5

Notes: N = 1297 covering Australia (496), United Kingdom (355), Hong Kong (260) and United States (186).

The age of wines varies from one to seven years. The most dominant varieties are shiraz (38.5%), chardonnay (20.4%) and cabernet sauvignon (16.9%). The main wine regions are different region cool climate wines (31.2%), Barossa Valley (16.1%) and Margaret River (14%). Wines available in Australia make up (38%) of the sample, United Kingdom (27%), Hong Kong (20%) and United States (14%).

The choice of functional form for the hedonic price function has commanded considerable attention in the literature (e.g., Cropper, Deck and McConnell 1988). We explicitly consider five commonly employed functions outlined in table 2 and choose among them using theoretical and empirical considerations. Rosen (1974) theoretically questions the use of the linear specification as it implies the possible repacking of a good using different attribute contributions in nonmeaningful ways. Further the linear specification implies a constant marginal price for the attribute. For marginal offer function estimation this implies marginal prices take on as many values as there are distinct markets, in our case only four. Rasmussen and Zuehlke (1990) point to the theoretical limitations of the log-linear specification. For the log-linear specification, marginal attribute prices are just product prices scaled by different constants for each market. This is possibly too restrictive. The other three forms (log-log, quadratic and log-quadratic) are more theoretically attractive as marginal prices also explicitly depend on attribute levels and can either be increasing or decreasing in attribute levels.

Table 2. Hedonic Functional Forms

	Equation	Marginal Attribute Price for X_1
Linear	$P = \alpha_1X_1+\alpha_2X_2$	α_1
Log-Linear	$\ln(P) = \alpha_1X_1+\alpha_2X_2$	α_1P
Log-Log	$\ln(P) = \alpha_1\ln(X_1)+\alpha_2\ln(X_2)$	α_1P/X_1
Quadratic	$P = \alpha_1X_1+\alpha_2X_2+ \alpha_3(X_1)^2+\alpha_4(X_2)^2+\alpha_5X_1X_2$	$\alpha_1+2\alpha_3X_1+ \alpha_5X_2$
Log-Quadratic	$\ln(P) = \alpha_1X_1+\alpha_2X_2+ \alpha_3(X_1)^2+\alpha_4(X_2)^2+\alpha_5X_1X_2$	$(\alpha_1+2\alpha_3X_1+ \alpha_5X_2)P$

Notes: P = price, X_1 = quality rating, X_2 = vintage years. Dummy variables for variety and region only enter as linear terms and each equation contains a constant and error term.

The RESET specification test has been found to usefully discriminate among various linear and log specifications (Godfrey, McAleer and McKenzie 1988). RESET tests for the five functional forms and four markets are presented in table 3. The log-quadratic specification is not rejected for any country, while the log-linear specification is not rejected for two of the four markets. The linear, log-log and quadratic specifications are all rejected by the RESET test, with the log-log specification being the most strongly rejected. Goodness of fit and model selection statistics (adjusted R^2, Bayesian information criterion (BIC) and the Akaike information criterion (AIC)) based on raw prices for the functional forms supported the quadratic and log-quadratic and specifications as the best performing. On the basis of the RESET tests and model selection measures the log-quadratic form is the preferred specification and is highlighted below with references made to the results from other functional forms.[7]

Table 3. Hedonic Price Functions: RESET

	N	Linear	Log-Linear	Log-Log	Quadratic	Log-Quadratic
Australia	496	3.74***	1.99**	5.44***	2.16**	-0.08
United Kingdom	355	2.29**	1.54	4.50***	2.27**	0.87
Hong Kong	260	3.37***	2.34**	3.63***	2.35**	-0.77
United States	186	3.20***	0.95	3.29***	2.35**	0.77

*Notes: RESET is the robust Ramsey specification error test using the squared predictions. ***, **, * denotes statistically significant at the 1%, 5% and 10% levels respectively*

[7] As an additional robustness check we estimated quantile regression models for the hedonic price functions using the 25%, 50% and 75% quartiles. For the log-quadratic form, of the 68 bootstrap F tests for testing the equivalence of quartile estimates (one test for each country and attribute combination), only two (2.9% of all tests) indicated significant differences. These results point to the constancy of the estimated premiums and discounts across different price quartiles.

An important issue for the accurate identification of the marginal offer (cost) function is the existence of separate distinct price functions across markets as illustrated in figure 1. Chow tests are presented in table 4 to examine whether the estimated parameters are statistically the same across the four markets using the log-quadratic form. Pairwise market comparisons indicate that parameters are statistically different among all markets except for United Kingdom and United States. Similar results are obtained for the other functional forms. In summary, the Chow tests possibility point to sufficiently significant differences in parameters across markets to justify the multi-market estimation of the marginal offer function.

Table 4. Hedonic Price Functions: Chow-Tests

	Log-Quadratic
Australia vs Hong Kong	18.2***
	F16,522)
Australia vs United States	6.25***
	F(16,510)
Australia vs United Kingdom	13.0***
	F16,542)
United Kingdom vs Hong Kong	2.44***
	F(16,493)
United Kingdom vs United States	1.40
	F(16,450)
Hong Kong vs United States	1.69**
	F(16,376)

Notes: Chow Test employs cluster robust (by wine_id) standard errors.
****, **,* statistically significant at the 1%, 5% and 10% levels respectively.*

5. Results

The estimates for first stage hedonic price function (eqn (4)) for the log-quadratic specification and each of the markets are presented in table 5. There is some variability in quality rating and vintage year effects across markets. The proportionate marginal impact of quality on prices is largest for Australia (0.132) and smallest for the United Kingdom (0.089). While for vintage years the United States has the largest proportionate price impact (0.354) and Hong Kong (0.234) the lowest. For varieties, chardonnay and pinot noir have the largest positive impact on prices and cabernet sauvignon the largest negative impact on prices.[8] For regions the Barossa Valley and Yarra Valley have the largest positive price impacts and wines from Margaret River and other warm climate regions the largest negative price impacts. Once again, the price impacts for regions and varieties appear to differ across markets.

Summary statistics for the estimated marginal prices using eqn (5) and table 2, for the log-quadratic form for all four markets are presented in table 6.

[8] For variety and region, dummy variables are defined such that estimates are deviations from average prices rather than a control group, see Kennedy (1986).

Table 5. Hedonic Price Functions: Log-Quadratic Form

	Australia	United Kingdom	Hong Kong	United States
Quality Rating	-1.834***	-1.301***	-1.998***	-1.129***
	(-5.28)	(-3.86)	(-4.87)	(-2.85)
Vintage Years	0.038	-0.163	-1.566**	-0.831
	(0.06)	(-0.22)	(-2.44)	(-0.97)
(Quality Rating)^2	0.0105***	0.0074***	0.0110***	0.0065***
	(5.49)	(4.01)	(4.91)	(3.01)
(Vintage Years)^2	-0.0223	-0.0352**	-0.0450***	-0.0558**
	(-1.63)	(-2.14)	(-2.95)	(-2.43)
Quality*Vintage Years	0.0038	0.0063	0.0215***	0.0155
	(0.53)	(0.75)	(2.85)	(1.58)
Varieties				
Cabernet Sauvignon	-0.104**	-0.105*	-0.089	-0.246***
	(-2.22)	(-1.94)	(-1.29)	(-3.54)
Chardonnay	0.090**	0.084*	0.100	0.240***
	(2.12)	(1.77)	(1.51)	(2.80)
Pinot Noir	0.101**	0.162***	0.099	0.215**
	(2.14)	(2.94)	(1.39)	(2.27)
Riesling	0.044	0.024	0.177*	-0.028
	(0.65)	(0.34)	(1.73)	(-0.14)
Shiraz	-0.051	-0.066*	-0.097*	-0.093
	(-1.54)	(-1.69)	(-1.79)	(-1.64)
Regions				
Barossa Valley	0.079	0.162**	0.077	0.110
	(1.36)	(2.54)	(0.97)	(1.18)
Clare Valley	-0.003	-0.044	0.041	0.153
	(-0.05)	(-0.58)	(0.68)	(0.92)
Cool Climate	0.050	0.059*	0.007	-0.003
	(1.58)	(1.65)	(0.14)	(-0.06)
Margaret River	-0.097*	-0.125**	-0.065	-0.166*
	(1.97)	(-2.33)	(-0.91)	(-1.80)
McLaren Vale	-0.026	-0.069	-0.028	0.061
	(-0.52)	(-1.09)	(-0.46)	(0.76)
Warm Climate	-0.097*	-0.152**	-0.119	-0.271***
	(1.93)	(-2.17)	(-1.28)	(-3.02)
Yarra Valley	0.102	0.034	0.122	0.240*
	(1.31)	(0.43)	(1.24)	(1.83)
constant	82.7***	59.7***	93.3***	51.9***
	(5.23)	(3.90)	(4.96)	(2.83)
R^2	0.563	0.496	0.491	0.577
N	496	355	260	186
Marginal Impact of Quality (at means)	0.132	0.089	0.107	0.115
Marginal Impact of Vintage (at means)	0.293	0.270	0.234	0.354

*Notes: ***, **, * denotes statistically significant at the 1%, 5% and 10% levels respectively. Robust t-ratios reported in parentheses. .*

Table 6. Marginal Prices Summary Statistics: Log-Quadratic Form

	Mean	Standard Deviation	Minimum	Maximum
All Countries				
Quality Rating	7.056	8.389	-5.793	80.75
Vintage Years	14.18	11.42	-13.67	95.47
Chardonnay	5.975	6.271	0.788	66.41
Barossa Valley	5.510	4.687	0.691	39.12
Australia				
Quality Rating	7.026	8.704	-2.776	80.75
Vintage Years	12.71	10.10	2.422	95.47
Chardonnay	4.084	3.401	0.788	31.44
Barossa Valley	3.580	2.981	0.691	27.55
Hong Kong				
Quality Rating	8.587	10.22	-5.793	64.20
Vintage Years	14.24	13.14	-13.67	87.23
Chardonnay	6.093	4.292	1.537	27.96
Barossa Valley	4.660	3.283	1.176	21.38
United Kingdom				
Quality Rating	5.757	5.814	-1.676	39.20
Vintage Years	13.67	8.706	-5.361	56.90
Chardonnay	4.382	2.959	0.964	20.44
Barossa Valley	8.388	5.665	1.845	39.12
United States				
Quality Rating	7.747	8.532	-0.863	51.13
Vintage Years	18.95	15.01	-6.483	77.86
Chardonnay	13.89	11.16	2.226	66.41
Barossa Valley	6.353	5.101	1.018	30.37

Statistics for marginal prices are provided for quality rating, vintage years and a representative variety (chardonnay) and region (Barossa Valley). For all countries combined, the sample mean marginal price of vintage years ($14.18) is double that of quality ratings ($7.06). These values are not directly comparable given their different units of measure. In terms of a sample standard deviation increase, the mean marginal price of vintage years is $13.70 which is less than the mean marginal price of quality $22. Chardonnay ($6) and Barossa Valley ($5.50) have approximately equal mean marginal prices.

Some differences are apparent when comparing the marginal prices across countries in table 6. In terms of sample means, for quality rating marginal prices are highset for Hong Kong ($8.59) and lowest for United Kingdom ($5.76). For vintage years marginal prices are highest for United States ($18.95) and lowest for Australia ($12.71). For Chardonnay marginal prices are highest for United States ($13.95) and lowest for Australia ($4.08). While for Barossa Valley marginal prices are highest for the United Kingdom ($8.39) and lowest for Australia ($3.58). In general there appears to be no systematic similarities across countries for the sample mean of marginal prices.

It should be noted for the quality rating and vintage years the preferred log-quadratic form produces a number of negative marginal pries. The issue is more pronounced for quality ratings (5.0%) than for vintage years (1.1%). More frequent negative marginal prices are produced by the quadratic form, (12.0%) for quality ratings and (2.1%) for vintage years. Economically, negative marginal prices are not meaningful for desirable and more costly to produce attributes.[9]

Given the marginal price estimates from eqn (5) (summarized in table 6) and the attributes employed for eqn (4) (summarized in table 5), to estimate the inverse supply or marginal offer function (eqn (7)) the supply shifters (Y_2) need to be specified. As previously indicated the number of cases of the wine made or producer size more generally, has been used extensively in previous hedonic price functions. In the Australian context, individual wines cases produced data is 'commercial in confidence' and not generally available, however, the size of the producer measured by the number of cases produced for all wines is available. ANZWID (2019) collects producer size data using ranges of cases produced and this necessitates the use of categories for producer size variable in estimation.

Oczkowski (2016a) used a number of other producer specific variables for analyzing the producer fixed effects on Australian wine prices. These relate to producer experience, producer reputation and the use of multi-brands by conglomerates. Producer experience is postulated to have possibly two opposing effects on wine prices (Roma et al 2013). Older firms may be strategically better positioned to serve the market as they have a well-established production and market knowledge, while younger firms may be more dynamic and innovative and better placed to explore new market opportunities. We also employ a producer rating measure from the AWC (where 5.5 points is given to a 5 red star winery) which captures the quality of the range of wines produced by an individual producer. In part, it is suggested a higher producer reputation can command wine premiums from consumers who lack information about quality. In Australia, a small number of large conglomerates exist which produce a range of wine brands. For our sample only three exist which occur with any great frequency. Potentially these conglomerates could employ the relation among brands to influence prices for individual brands (wineries). Producer experience and the use of multi-brands are based on data collected from ANZWID (2019). The summary statistics of the employed producer variables is provided in table 1 and for dummy

[9] Negative marginal prices have also been estimated for desirable attributes in other studies, see for example, Zabel and Kiel (2000) and Netusil, Chattopadhyay and Kovacs (2010). In some cases a rational explanation is provided for negative prices, in other cases claims of mis-specification and sampling error are offered as explanations. Using all marginal prices for marginal offer estimation is the most common practice and appears to perform better than omitting negative observations in previous studies.

variables, estimates are interpreted as deviations from average marginal prices rather than a control group.

As articulated by Epple (1987) and subsequently recognized by most studies examining marginal prices, the level of attributes are chosen optimally based on marginal prices and as such are endogenous in eqn (7). This requires the use of techniques such as instrumental variables (IV) to consistently estimate the marginal offer function. It is important to develop both theoretically justified and empirically supported instruments to generate accurate estimates for eqn (7). As instruments we employ consumer quality ratings from Vivino (www.vivino.com), these alternative ratings have been shown to have similar explanatory power for explaining prices to AWC ratings (Oczkowski and Pawsey 2019). We also employ a series of weather variables as instruments. Oczkowski (2016b) shows for Australian wines, prices are better explained by quality ratings than weather fluctuations directly and so the impact on weather on prices is better captured through quality ratings. We employ the following weather variables: harvest, growing season and winter rain; temperature differential; growing season temperature; growing degree days and mean January temperature; with interactions for the late ripening varieties. Both consumer ratings and weather information are not expected to have any additional explanatory power in determining prices over and above the attributes but are still likely to be highly correlated with the attributes and hence are potentially good candidates for instruments. As suggested by Palmquist (2005) we also examined dummy variables identifying the separate markets and their use as interactions, as instruments. These proved to be unsuccessful, invariably resulting in the failing of over-identification tests.

All first stage partial F statistics exceed ten and average 31.8, hence the instruments are not weak and IV estimates are likely to lead to estimation efficiency improvements over ordinary least squares (OLS) (Cameron and Trivedi 2005). Also for the employed instruments, the Hansen J cluster robust over-identifying test (table 7) indicates the specification and/or instruments are valid in the employed models. The cluster robust score test (table 7) strongly rejects the assumption that the regressors are exogenous in all models which also suggests the IV estimates are preferred to OLS estimates.

Standard linear inverse supply functions for four attributes using marginal prices from the log-quadratic first stage hedonic functional form[10] are presented in table 7.

[10] These estimates use all marginal prices from all four markets, including negative values. Excluding negative marginal prices made no demonstrable change to estimates.

Table 7. Inverse Attribute Supply: Log-Quadratic Hedonic Marginal Prices

	Quality Rating Marginal Prices	Vintage Marginal Pries	Chardonnay Marginal Prices	Barossa Valley Marginal Prices
Quality Rating	2.158***	2.990***	1.025***	0.794***
	(5.06)	(4.15)	(3.30)	(2.92)
Vintage Years	4.486***	2.576	3.167***	2.732***
	(3.74)	(1.26)	(3.35)	(3.35)
Varieties				
Cabernet Sauvignon	-12.409**	-20.639**	-8.790**	-8.327**
	(-2.23)	(-2.25)	(-2.14)	(-2.39)
Chardonnay	-1.234	-1.717	-0.479	-0.806
	(-0.55)	(-0.49)	(-0.31)	(-0.61)
Pinot Noir	6.060*	10.398*	1.045	4.281**
	(1.85)	(1.87)	(1.64)	(1.97)
Riesling	-1.589	-7.457	-2.354	-1.476
	(-0.52)	(-1.42)	(-1.00)	(-0.73)
Shiraz	4.205	7.911*	3.173*	2.832*
	(1.64)	(1.88)	(1.71)	(1.83)
Regions				
Barossa Valley	-3.566	-8.721*	-3.032	-2.614
	(-1.32)	(-1.90)	(-1.46)	(-1.54)
Clare Valley	8.740*	19.037**	8.418**	6.110*
	(1.69)	(2.14)	(2.12)	(1.82)
Cool Climate	-0.848	-0.902	-0.568	-0.208
	(-0.80)	(-0.53)	(-0.76)	(-0.33)
Margaret River	2.843	4.998	1.404	2.034
	(1.06)	(1.15)	(0.73)	(1.23)
McLaren Vale	-0.666	-1.614	-0.472	-0.896
	(-0.42)	(-0.60)	(-0.40)	(-0.91)
Warm Climate	-1.305	-2.975	-1.152	-1.081
	(-0.47)	(-0.68)	(-0.65)	(-0.70)
Yarra Valley	-0.674	-0.460	-0.495	-0.955
	(-0.28)	(-0.12)	(-0.30)	(-0.63)
Producer Variables				
Size (1000 cases)				
0 - 19.9	-2.135***	-2.784**	-1.430**	-1.066**
	(-2.74)	(-2.08)	(-2.48)	(-2.13)
20 - 49.9	0.432	0.265	0.709	0.477
	(0.50)	(0.19)	(1.07)	(0.86)
50 - 99.9	-0.416	-0.290	-0.270	-0.116
	(-0.40)	(-0.17)	(-0.37)	(-0.17)
100-499.9	1.710	2.003	0.408	0.341
	(1.13)	(0.78)	(0.36)	(0.35)
500 or over	5.323***	7.785**	3.677***	2.667**
	(2.67)	(2.38)	(2.64)	(2.21)
Established (Year)				
After 2000	1.409*	1.932	1.036*	0.976*
	(1.66)	(1.34)	(1.65)	(1.78)
2000 or Before	-0.452*	-0.620	-0.332*	-0.313*
	(-1.66)	(-1.34)	(-1.65)	(-1.78)
Conglomerates				
Accolade Wines	-2.688	-6.995*	-3.767**	-2.649*
	(-1.18)	(-1.72)	(-2.09)	(-1.66)
Pernod Ricard	6.022	6.998	4.410	3.272
	(1.60)	(1.12)	(1.56)	(1.34)
Treasury Wine Estates	1.267	3.681	2.347	1.992
	(0.38)	(0.66)	(0.88)	(0.87)
Non-conglomerate wineries	-0.127	-0.167	-0.121	-0.105
	(-0.63)	(-0.47)	(-0.73)	(-0.73)
Producer Reputation Rating	-1.898	-2.739	-0.656	-0.499
	(-1.25)	(-1.05)	(0.58)	(-0.51)
constant	-194.0	-1255.7***	-93.16***	-71.94***
	(-5.85)	(-4.63)	(-3.94)	(-3.47)
GR^2	0.433	0.372	0.273	0.342
OIV Test ($\chi^2(9)$)	6.50	3.00	6.47	6.30
Exogeneity Test (F(12, 569))	5.61***	10.9***	6.79***	8.55***

*Notes: ***, **, * denotes statistically significant at the 1%, 5% and 10% levels respectively. N = 1297. Dependent variable log-quadratic marginal hedonic prices. Linear functional forms. Cluster robust t-ratios (based on wine id) reported in parentheses. GR^2 is the generalized R^2 for IV estimated models. OIV is the Hansen J cluster robust over identifying test based on wine id. The exogeneity test is the cluster robust score test statistic, based on wine-id.*

For *quality rating* as expected the impact of the own attribute is positive and significant indicating the convexity of the total cost function and a positively sloped marginal cost curve. Specifically, for a one quality rating point increase the marginal cost of producing a wine with an additional quality point is \$2.20. For a sample standard deviation increase in quality this implies an increase in the marginal cost of quality of \$6.90.Vintage years is positive indicating that for an additional vintage year the marginal cost of producing additional quality increases by \$4.50. For a sample standard deviation increase in vintage years this implies an increase in the marginal cost quality of \$4.30, which is less than that for the standard deviation increase in quality. For varieties, the production of pinot noir and shiraz increase the marginal cost of quality, while cabernet sauvignon reduces the marginal cost. For regions, grapes from the Clare Valley increase the marginal cost of quality while those from the Barossa Valley reduces it the most.

The main impacts of producer size on the marginal cost of quality occur at the extremes. Compared to sample mean prices, an important negative impact (-\$2.10) is estimated for very small producers (less than 20,000 cases) and a large important positive impact (\$5.30) for very large producers (500,000 cases or over). For wine made by producers within these extreme sizes, marginal costs do not significantly differ from the sample mean marginal costs. These results run counter to the standard economies of scale argument used in previous wine studies where increased producer size leads to a fall in wine prices. [11]

In terms of the other producer related estimates for quality rating it appears that younger producers are possibly less capable of achieving productive efficiency compared to mean sample prices, and are associated with higher marginal costs. Conversely, older producers benefit from reduced marginal costs. Of the conglomerates it appears wines from Pernod Ricard may incur higher marginal costs, even though the point estimate appears large (\$6) it is not statistically significant. Producer rating does not appear to have any demonstrable impact on marginal costs.

In general these results for quality rating and the log-quadratic form for marginal prices are similar to estimates from the log-linear and log-log forms for marginal prices. The same statistically significant results for producer size and producer experience occur. The results from the linear form for marginal prices are not particularly meaningful given only four different values for marginal prices in the data set. Estimates from the quadratic model differ however from the log forms. The general tendency for a positive relation between producer size and marginal cost

[11] It is worth noting these different findings between marginal cost and hedonic price estimates for producer size are not due to the data set employed but possibly the employed technique. When the producer variables are also entered into the hedonic price functions (eqn (4)): the estimates for very small producers (less than 20,000 cases) is statistically significant (at the 5% level) and positive for Australia, Untied States and United Kingdom. While the estimate for very large producers (500,000 or more cases) is always negative but not statistically significant.

is still evident for the quadratic model. For quadratic marginal prices, producer experience and conglomerates are not important, however a significant and negative impact is estimated for producer rating.

The estimates for the marginal prices of *vintage years* (table 7) largely follow those for the quality rating. While a positively sloped marginal cost curve for vintage years is established it is not statistically important. A higher quality rating is associated with higher marginal costs for vintage years. In standard deviation terms, the increase in the marginal cost of vintages years for a change in vintage years is $2.50, which is much lower than the increase in marginal cost of vintage years for a standard deviation change in quality of $9.30. The positive cross attribute estimate for the marginal cost of vintage years given a change in quality ($3) establishes some symmetry with the positive impact of vintage years on the marginal cost of quality ($4.50). The negative relation between producer size and marginal attribute price for vintage years is still present at the extremes, however, the lower marginal costs of experienced producers is not statistically significant. For conglomerates Accolade Wines has significantly lower marginal costs, while Pernod Ricard's point estimates still remain high. These log-quadratic marginal price results are largely the same as results from the log-linear and log-log marginal price forms. However, again the quadratic form produces different results: vintage years is highly significant and negative, this implies a downward sloping marginal cost curve; and no producer variables are statistically important except for a negative impact for Accolade Wines. In part the poor performance of the quadratic model may be due to its rejection by the RESET test.

The representative variety (chardonnay) and region (Barossa Valley) marginal price estimates in table 7 are presented for illustrative purposes only. These regressors are dummy variables and hence strictly do not have the standard marginal price impetration but rather a displacement of offer prices occurs. Both equations suggest a statistically insignificant negative displacement occurs for own attributes. Quality rating and vintages years are both positive and significant, implying the displacement cost of using either chardonnay or grapes form the Barossa Valley increases as both the quality rating and vintage years increases. The inverse producer size impact at the extremes for costs still occurs, younger producers again have higher costs while a negative impact for Accolade Wines is estimated. Similar results again are found for the log-linear and log-log forms. For the quadratic form neither quality rating nor vintage year are statistically significant, however the inverse extreme producer size impact is identified for chardonnay only.

6. Discussion and Conclusion

This paper presents inverse supply or marginal offer (cost) function estimates for wine using the second stage of the Rosen (1974) hedonic framework. This is achieved by using data for similar wines across four different consumer markets. Unlike some previous hedonic price wine studies, producer specific variables have been excluded from hedonic price estimation to generate marginal prices for the second stage analysis where both attributes and producer specific variables are employed. The results point to a series of interesting findings.

For the two meaningful continuously measured attributes of quality rating and vintage years, positive sloped marginal cost functions were identified with positive cross attribute effects. Results imply the additional costs of producing better quality wines is higher a wine's age is increased, while the additional costs of producing older wines is higher as quality is increased.

The impact of producer size on marginal costs is found to be counter to expectations. Compared to sample mean marginal costs, for very small producers marginal costs are lower and for very large producers marginal costs are higher. For producers in-between these extremes marginal costs are not appreciably different from sample mean costs. These results are mainly due to the two-stage method employed as direct hedonic function estimation with producer size establishes the standard inverse size relation with price for this data set. A number of explanatory comments can be made. First, producer size estimates from hedonic price functions relate to the change in product price and not to the change in marginal attribute price/cost and hence estimates are not directly comparable.

Second, the standard economies of scale argument may be more directly relevant when using quantity sold as the size measure. In contrast, the use of producer size needs to recognize the existence of an entire product line where the quality sold for a specific high quality wine (typical of our data set) may be very small for a large of producer. In general, very small producers tend to employ their own estate grown grapes and in the Australian context over half of small producers use outside contract winemaking (ACCC 2019). As a consequence the higher costs associated with small scale production may be somewhat mitigated as many producers avoid the outlay of large capital costs and the need cover significant fixed costs associated with small scale wine making. In contrast, very large producers need to efficiently develop skills in producing both high volume low quality and low volume high quality wines and the economies of scale gained for low quality production may not always translate to high quality wines. Third, the unexpected producer size results may be the outcome of the inappropriate prefect competition assumption of the Rosen (1974) framework and that producer size is more appropriately specified directly in the hedonic price function reflecting elements of price making behaviour. In the Australian context over 2500 winemakers exist (ACCC 2019), the largest four conglomerates produce approximately 28% of total output (IBISWorld 2020). IBISWorld classifies the Australian wine production industry as being highly competitive. The bulk of wine production however occurs at the low price points with only approximately 17% of bottled wine sales occurring for wines above $15, which reflects our data set (Wine Australia 2019b). In other words, for our premium wine data set where relatively low volumes are produced by over 2000 producers, the influence of large producers may not be particularly strong, however, the existence of market power impacting prices should not be totally ruled out.

Some of the other results are also worthy of comment. We have found older more established producers are capable of producing attributes at lower marginal costs. Effectively, well-established producers may be further down the learning curve and hence able to produce wines at lower marginal costs for a wine's quality and age. While, in contrast to some hedonic price function estimates, we do not find producer reputation to have any noticeable impact when employing marginal prices.

In conclusion, as this paper appears to provide the first application of the two-stage Rosen (1974) framework for wines, it is clearly important to see if these results gained for Australian wines translate to wines produced by other countries where wines are also sold in different markets. In particular, applications of the methodology to countries where quantity sold data for each wine are available could be usefully performed.

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