Estimating the Demand for Sensory Quality – Theoretical Considerations and an Empirical Application to Specialty Coffee

Schätzung der Nachfrage nach sensorischer Qualität – theoretische Überlegungen und empirische Anwendung auf Spezialitätenkaffee

Ramona Teuber
Justus Liebig University Giessen, Germany

Abstract

An increasing product differentiation coupled with an increasing availability of electronic data has boosted the number of hedonic price analyses applied to food and agricultural products. Most of these studies estimate the first stage of a complete two-stage model as proposed by ROSEN. However, there are also a few studies that estimate the second stage, i.e. supply and demand functions for characteristics. The present paper reviews both the theoretical and applied literature on Rosen's two-stage model in the context of food and agricultural economics. Based on these findings, a theoretical model for specialty coffee auction data is proposed and tested empirically. The empirical model comprises non-linear hedonic bid functions at stage one and an inverse demand function for one characteristic, the sensory quality score (SQS), at stage two. The first-stage results indicate a high variability of the marginal price of the SQS across different auctions, i.e. across time and space. The second-stage results suggest that the marginal prices of the SQS increased in the analysed period 2003-2009 and that country-of-origin and buyer effects are important. The highest marginal prices are paid for Rwandan and Honduran coffee. At first glance, this is surprising, since at the first stage Honduran coffees are almost always sold at discounted prices compared to coffees of other origins. However, it seems that the SQS is a much more important quality cue for a coffee origin with a low reputation than for a coffee origin with a well-established reputation in the marketplace.

Key words

two-stage hedonic models; implicit prices; sensor quality score; specialty coffee

Zusammenfassung

Die zunehmende Produktdifferenzierung und Verfügbarkeit elektronischer Datensätze hat zu einer stetig steigenden Zahl hedonischer Analysen für Agrarprodukte und Lebensmittel geführt. Die Mehrzahl dieser Studien schätzt hierbei die erste Stufe des von ROSEN theoretisch hergeleiteten zweistufigen hedonischen Modells. Es gibt jedoch auch einige wenige Studien, die auch die zweite Stufe, d.h. Angebots- bzw. Nachfragefunktionen für Eigenschaften schätzen. Der vorliegende Beitrag analysiert die bisherige theoretische und empirische Literatur zu zweistufigen hedonischen Modellen im Kontext der Agrar- und Ernährungsökonomie und leitet darauf basierend ein theoretisches und empirisches zweistufiges Modell für Spezialitätenkaffee ab. Das empirische Modell besteht aus einer nichtlinearen hedonischen Preisfunktion auf der ersten Stufe und einer inversen Nachfragefunktion für eine Produkteigenschaft, der sensorischen Qualitätspunktzahl (SQS), auf der zweiten Stufe. Die Ergebnisse der ersten Stufe weisen eine hohe Variabilität der impliziten Preise dieser Eigenschaft sowohl über die Zeit als auch über Regionen hinweg nach. Die Ergebnisse der zweiten Stufe belegen einen Anstieg der impliziten Preise der sensorischen Qualitätspunktzahl in der betrachteten Zeitperiode 2003-2009 und signifikante Anbauländer- und Käufereffekte. Kaffee aus Honduras erzielt hierbei neben Kaffee aus Rwanda die höchsten impliziten Preise. Dieses Ergebnis erscheint zunächst überraschend, da Kaffee aus diesen Ursprungsländern typischerweise auf der ersten Stufe diskontiert wird. Auf den zweiten Blick erscheint dieses Ergebnis aber durchaus plausibel. Für Kaffee aus Ländern mit einer bisher nur gering ausgeprägten Reputation für Qualität ist die Qualitätsbewertung signifikant bedeutsamer als für Kaffees aus Ländern mit einer etablierten Reputation für Qualität.

Schlüsselwörter

zweistufige hedonische Modelle; implizite Preise; sensorische Qualitätsbewertung; Spezialitätenkaffee

1 Introduction

A steadily increasing product differentiation paired with an increasing electronic data availability has boosted the number of studies applying hedonic price analyses to food and agricultural products (DONNET et al., 2008; HUANG and LIN, 2007; KRISTOFERSSON and RICKERTSEN, 2007; WARD et al., 2008). The aim of these studies is to investigate which characteristics are most important in determining product prices and this is done by estimating implicit prices for characteristics using multiple regression analysis. Based on these implicit prices, it is possible to infer which characteristics are more highly priced in the market.

However, it has to be kept in mind that the estimated marginal characteristic prices are the result of supply of and demand for characteristics. Therefore, marginal prices are not constant over time and space and the question that arises is what determines marginal characteristic prices. Several approaches have been discussed in the literature regarding how to estimate the underlying supply and demand functions for characteristics. Nevertheless, it seems that there is still no real consensus in the scientific community on which is the most adequate approach to estimate a complete two-stage hedonic model.

Given this background, the present paper pursues the following objectives. First, its aim is to review the different two-stage hedonic modelling approaches discussed in the literature highlighting estimation problems and the suggested solutions. Second, based on these findings, a theoretical model for the estimation of a two-stage hedonic model for auction data will be developed. Finally, the theoretical model will be tested empirically by using internet auction data for specialty coffee from nine different countries covering the period 2003-2009.

The specialty coffee market was chosen for several reasons. To begin with, it is a market which has experienced an enormous increase in product differentiation in recent years. Moreover, despite the fact that it is still a niche market, it has grown tremendously compared with the stagnating mass coffee market. Hence, it is of great interest to coffee producers to know which characteristics are highly valued in the marketplace. Previous studies on specialty coffee found – using pooled auction data for high-quality coffee – significant price impacts of the quality proxied by a sensory quality score (SQS) and significant country-of-origin effects (DONNET et al., 2008; TEUBER, 2010). Whereas these studies highlight the importance of the SQS on the closing auction price, none of them has investigated which factors determine the marginal price of the SQS. Thus, the main research question addressed in the present paper is whether the SQS is valued differently across auctions and, if so, which determinants can explain these differences.

2 Valuing Diversity – A Review of the Hedonic Methodology

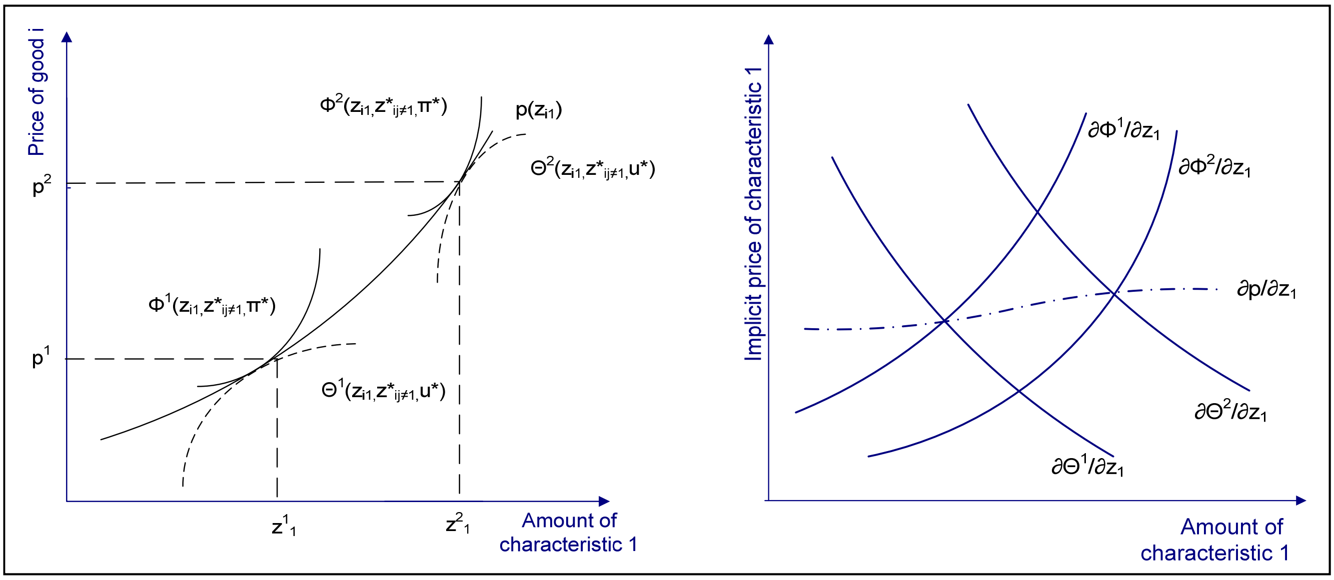
In the context of product differentiation and product demand it is often convenient to think of goods in terms of their location on a map of characteristics. Consequently, whether one product is more desirable than another is determined by its location in the characteristics space (ROSEN, 2002). Hence, if we analyse the demand for and the price formation of differentiated agri-food products, it is essential to include characteristics in order to derive plausible and reliable results. Valuing characteristics for which no explicit market exists and identifying supply and demand functions for these characteristics are the core of the hedonic methodology. The idea that consumers have preferences for characteristics instead of goods has been established by GORMAN (1956), LANCASTER (1966) and ROSEN (1974), and since then a large number of studies has been published on this subject. The following sections provide an overview of the main aspects of hedonic pricing models[1], covering theoretical and applied research.

2.1 ROSEN'S Two-Stage Model

The basic idea of hedonic pricing models is that the price of a unit of a market good varies with the set of characteristics it possesses and, thus, price differences between goods reflect differences in the utility-bearing characteristics. Accordingly, each good i has a quoted market price and is associated with a vector of characteristics $z_i = (z_{i1},...,z_{in})$, with z_{ij} being the quantity of characteristic j $(j = 1,2,…,n)$ embodied in good i. This leads to the hedonic price function

[1] Sometimes authors use the term characteristic models instead of hedonic models (i.a. BLOW et al., 2008). In most cases the terms can be used interchangeably.

Figure 1. The Market Equilibrium in Hedonic Markets



Source: modified according to ROSEN (1974): 39, 43 and 49

$p_i = p(z_i) = p(z_{i1},...,z_{in})$, which conveys market prices and characteristics. ROSEN (1974) described how this hedonic price function (HPF) is generated in a competitive market. Analogously to the traditional utility-maximization model, utility functions have to be maximized subject to the budget constraint (ROSEN, 1974).

Assuming that preferences for the differentiated product are defined via the product's characteristics, the consumer's utility function $U(X, z_i)$ is a function of the characteristics embodied in the differentiated product and X, an aggregate of all other goods consumed. This utility function is maximized subject to the budget constraint

(1) $X + p(\mathbf{z}_i) = Y$

where $p(z_i)$ is the price of the differentiated good i and Y is income. From this utility function, which is concave in the characteristics, ROSEN (1974) derives a consumer's bid function $\Theta\,(z_{ij})$ by inverting the utility function holding all but the amount of characteristic j constant[2]:

(2) $\Theta = \Theta(z_{ij}; u(\alpha), y)$

with α being a taste parameter that parameterizes preference heterogeneity across consumers. The bid function represents consumer's willingness to pay (WTP) for different amounts of characteristic j given his preferences (α), income (y) and a certain utility level (u). Since consumers differ in terms of their preferences, income or both, each individual has got a different bid function. The counterpart to the bid function on the demand side is the offer function by suppliers. It is defined as:

(3) $\Phi = \Phi(z_{ij}; \pi, \beta)$

where β is a shift parameter reflecting underlying variables such as factor prices or production technologies and π is profit.

In equilibrium, consumer's marginal willingness to pay (MWTP) for an attribute must be equal to the marginal price which, in turn, must be equal to producer's marginal cost to provide the characteristic. Hence, the optimum condition can be expressed as:

(4) $\partial\Theta / \partial z_{ij} = \partial\Phi / \partial z_{ij} = \partial p \big/ \partial z_{ij} = p_j$

with p_j being the marginal price for characteristic j.

The fact that consumers and producers differ with respect to preferences (α) and technologies (β) respectively leads to multiple equilibria. These equilibrium points are identified by the HPF as illustrated in figure 1 (PALMQUIST, 1984; ROSEN, 1974). The left-hand side panel illustrates the bid functions of two consumers, who differ in α, that are matched with two suppliers, who differ in β, holding all other characteristics, income and utility constant. Consumers with taste

[2] In the literature the terms value function and indifference curve are sometimes utilized rather than the term bid function. However, they all refer to the same function.

preferences $\Theta^1(z)$ buy a product from seller $\Phi^1(z)$ containing amount z^1 of the characteristic 1, whereas consumers with a higher preference for the characteristic, i.e. $\Theta^2(z)$, purchase a good from seller $\Phi^2(z)$ containing amount z^2 of characteristic 1.

The right-hand side panel of figure 1 presents the market equilibrium in marginal terms, i.e. the first derivatives of the bid and offer functions of two different suppliers and buyers represent the compensated demand and supply function for characteristic *j,* respectively. The first partial derivative of the HPF with respect to *j* yields the set of the market equilibria.

In order to identify these underlying supply and demand functions empirically, ROSEN (1974) proposed a two-step procedure. In the first step, market data are used to estimate the HPF by choosing the functional form that fits the data best:

(5) $p_i = p(\mathbf{z}_i)$.

Computing the partial derivatives yields the marginal price of each characteristic *j*:

(6) $\partial p_i / \partial z_{ij} = \hat{p}_j$.

The estimated implicit marginal price $\hat{p}_j$ for a certain characteristic is the additional amount a consumer has to pay to move to a good with a higher level of that characteristic, other things being equal. These estimated marginal prices can be used to measure the WTP for a marginal change in the characteristic. However, if one is interested in the WTP for a non-marginal change in a characteristic, the inverse demand function for this characteristic has to be estimated. This is done in the following way by using the estimated marginal prices from stage one to estimate demand and supply functions for each characteristic *j* at stage two:

(7) $\hat{p}_j(z) = f_j(z_1,...,z_n,Y_1,e_{j1})$ (demand)

(8) $\hat{p}_j(z) = g_j(z_1,...,z_n,Y_2,e_{j2})$ (supply)

with j = 1,…,n, where Y_1 is a vector of income and consumer attributes[3] and Y_2 is a vector of factor prices and producer attributes; e_{j1} and e_{j2} are vectors of error terms. Equations (7) and (8) are the marginal bid and offer curves representing inverse supply and demand curves for each characteristic *j*. According to ROSEN (1974), this simultaneous system can be solved by simultaneous estimation methods such as two-stage least squares, using Y_1 and Y_2 as instruments.

One necessary prior condition for this two-stage procedure using data from a single market is that $p(z_i)$ is non-linear at stage one. If $p(z_i)$ is linear at stage one, the implicit marginal prices are constants leading to a zero variance across sample observations. However, in this case it is still possible to estimate marginal prices, which represent the individuals' MWTP for the characteristic. There are two special cases, in which a two-stage procedure is not needed. First, if all consumers are assumed to be identical with respect to income and preferences, all individuals have got the same inverse demand function, which is identified by the HPF. Second, if β is identical across all suppliers, the HPF is identical to the compensated supply function and there is no need to estimate the two functions specified above simultaneously (FREEMAN, 2003; ROSEN, 1974). Moreover, in consumer characteristics models in the tradition of GORMAN (1956) and MUELLBAUER (1974) it is assumed that consumers are price-takers. This assumption allows us to focus solely on the demand side without considering any simultaneity issues (BLOW et al., 2008).

Whereas the theoretical two-stage procedure seems to be straightforward, the empirical application can be rather tricky due to the fact that characteristics are usually part of a bundle of characteristics and cannot be traded separately. This bundling has important implications with respect to the law of one price and the budget constraint in hedonic models. In contrast to traditional utility maximization models, the law of one price does not necessarily hold in the characteristics space and the budget constraint is generally non-linear. This non-linearity stems from the fact that bundled goods are assumed to be indivisible and, hence, no arbitrage is possible. If consumers cannot unbundle and repackage different products to obtain a certain amount of the characteristic *j*, they have to search for the product that contains the desired amount of *j*. This can be illustrated by the following example. Let us suppose that a consumer searches for a new car and, for simplicity, that the only characteristic relevant in his purchase decision is the engine size. There is one car available with a 4000cc engine size and one car with a 2000cc engine, with the second car selling for less than half the price of the first. In this context, it is not feasible for the consumer to obtain a 4000cc engine by purchasing two 2000cc engines. This fact, which in many markets is most likely, implies that the law of one price does apply to the marketed good itself but

[3] ROSEN (1974) calls Y_1 and Y_2 the empirical counterparts of α and β introduced in equations (2) and (3).

not necessarily to the characteristics embodied in the good. Therefore, we usually expect to observe different implicit characteristics prices across varieties, implying a non-linear HPF with a non-constant price gradient (AGARWAL and RATCHFORD, 1980; ROSEN, 2002; ROSEN, 1974).

2.2 Critics, Explorations and Modifications of ROSEN's Two-Step Approach

BROWN and ROSEN (1982) demonstrated that the methodology proposed by ROSEN (1974) contains several pitfalls, which can lead to problems at stage two. They derived algebraically that, in the case of a linear-quadratic HPF and linear demand and supply functions, the second stage leads to parameter estimates that are identical to estimated coefficients at the first stage (BROWN and ROSEN, 1982). Put differently, they showed that the second-stage estimation can do no more than reproduce the coefficients from stage one, since no additional data beyond that already contained in the HPF is available at stage two (BROWN and ROSEN, 1982; FREEMAN, 2003).

Several ways have been discussed in the literature regarding how to overcome this problem in estimating demand functions for characteristics. One "technical" solution proposed by BROWN and ROSEN (1982) is to place restrictions *a priori* on the functional form. If the initial market equilibrium function is of order m in the z's, identification of structural demand and supply parameters is possible if the marginal price function is of order m-1 in the z's and the supply and demand functions are of order m-2 or less in the z's. This way of proceeding is considered to be rather problematic, because functional form restrictions seem to be arbitrary and not testable.

Another solution proposed by several researchers is to use data from multiple markets, i.e. spatially or temporally distinct markets (BARTIK, 1987; BROWN and ROSEN, 1982; EPPLE, 1987; KAHN and LANG, 1988). The line of argument is as follows. Underlying demand and supply functions for characteristics depend on the preferences of consumers and the technologies of producers that are characterized by a certain set of attributes. It is assumed that demand and supply functions are the same across markets, whereas the distribution of consumers and producers with a certain set of attributes is assumed to vary from market to market. Since the HPF is shaped by the distributions of consumers and producers, each market exhibits a different hedonic price function (EPPLE, 1987). Hence, the within-market variation is used to identify the HPF, and the between-markets variation is used to identify underlying supply and demand curves (KRISTOFERSSON and RICKERTSEN, 2004). In practice, temporal cross-section data, cross-section data from different regions or panel data seem to be appropriate for overcoming this type of identification problem in hedonic models. Although using data from different markets is considered to be the most promising way to identify hedonic models, recent publications by EKELAND et al. (2002, 2004) have demonstrated that multimarket data are no panacea for identifying hedonic models. ROSEN (2002) himself pointed out that the data requirements for the second-stage estimation are in most cases too demanding, since prices and attributes of goods are usually measured independently of the characteristics of buyers and sellers. Another problem arises with discrete instead of continuous variables. In such a case, it is not feasible to estimate the second stage as proposed by ROSEN (1974).

2.3 Empirical Two-Stage Models

Most of the empirical work on two-stage hedonic modelling has been carried out in the real estate literature and the non-market valuation of environmental amenities (BOCKSTAEL and MCCONNELL, 2007). Hedonic housing models are typically used to derive willingness-to-pay estimates for changes in environmental public goods such as air quality or recreational opportunities. MALPEZZI (2003) provides a review of hedonic property value models and the problems that usually arise in estimating these models. He concludes that the hurdles that must be tackled in estimating a structural hedonic model make a reliable estimation of demand for characteristics via two-stage models quite difficult. In most real estate studies it is assumed that the housing stock is given. This implies a totally inelastic supply of characteristics. Hence, if two-stage models are estimated, they are only concerned with the estimation of demand functions using either data from multiple markets, i.a. DAY et al. (2007) and ZABEL and KIEL (2000), or imposing functional form restrictions, e.g. CHATTOPADHYAY (1999). With regard to functional specifications, it is worth mentioning that semi-parametric and non-parametric methods have gained in importance in recent years. These methods allow for greater flexibility in estimating implicit prices. Empirical applications in the real estate literature are, for example, PACE (1993) and PARMETER et al. (2007) who apply kernel regressions on housing market data. Yet to the best of our

Table 1. Overview of Two-Stage Hedonic Models for Agri-Food Products

Author/Year	Type of Data	Hedonic Model	
		First Stage	Second Stage
EDMEADES (2007)	Survey data for bananas in Uganda, 2003, N=886 Cross-Section Data Producer/Consumer level	Log-linear specification	Supply functions for three variety attributes are estimated using 2SLS
KRISTOFFERSON and RICKERTSEN (2007)	Icelandic fish auction data, 1996-2000 N=289,406 Panel Data Set Wholesale level	Non-linear HPF and inverse input demand functions for characteristics are estimated simultaneously using a random coefficient (RC) model	
KRISTOFFERSON and RICKERTSEN (2004)	Icelandic fish auction data, 1998-2000 N=172,946 Panel Data Set Wholesale level	Linear HPF and inverse input demand functions for characteristics are estimated simultaneously using a random coefficient (RC) model	
BOWMAN and ETHRIDGE (1992)	Cotton spot market prices, U.S. market, 1977-1988, N=2,967 Temporal Cross-Section Data Producer level	Linear difference model with regional intercept and slope dummies	Inverse characteristics demand and ordinary supply functions for five attributes were estimated using SUR

Notes: HPF = Hedonic Price Function; N = Number of included observations; 2SLS = Two-Stage Least Squares; SUR = Seemingly Unrelated Regressions.
Source: own presentation

knowledge, there is no study estimating a two-stage model relying on non-parametric estimates.

There are also a few studies in which a two-stage hedonic model is estimated for agri-food products. Whereas the majority of hedonic first-stage studies have been carried out for wine, this is not the case for two-stage models, as can be seen from table 1. EDMEADES (2007) estimates a two-stage hedonic model for bananas in Uganda. This study is different from the other studies in as far as the product under consideration is a semi-subsistence crop which is produced and sold as well as consumed.

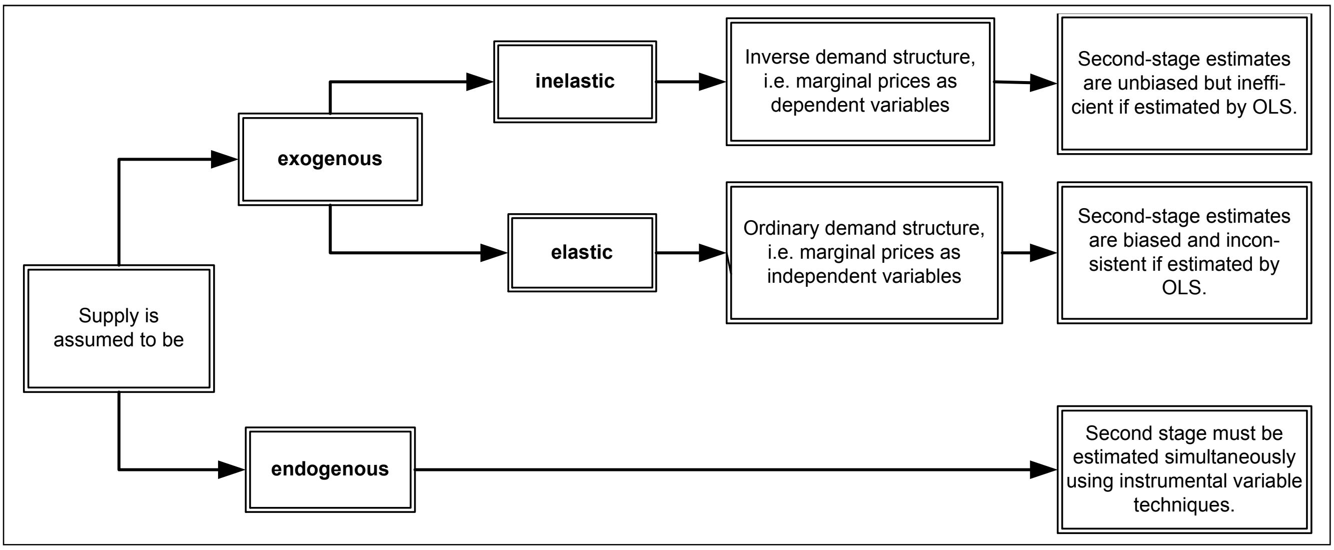
What all four studies have in common is that they use data from multiple markets in order to estimate the second stage. BOWMAN and ETHRIDGE (1992), hereafter BE, estimate a hedonic price function for each year by including regional intercept and slope dummies to obtain an average implicit price for each characteristic in each region and year. KRISTOFERSON and RICKERTSEN (2004, 2007), hereafter KR, treat data from each auction day as coming from a separate market and EDMEADES (2007) uses data from three different regions in Uganda.

In three studies, KR (2004, 2007) and BE (1992), it is assumed that the supply of characteristics is perfectly inelastic. KR justify this assumption by stating that the daily supplies of characteristics of fresh fish are given at the start of each auction day, since this supply cannot be changed during the auction day. Consequently, the supplied characteristics are treated as exogenous. This implies that the prices of characteristics are solely determined by demand, and the second stage is reduced to estimate an inverse demand system. KR (2004) identify three different scenarios that have to be distinguished in the context of two-stage hedonic models (see figure 2).

It is important to note that in the case of exogenous inelastic supply, second-stage estimates are efficient if first-stage estimates are equally accurate. However, unequal variances of estimated first-stage regression coefficients are quite likely and, therefore, second-stage estimates will be inefficient if estimated by OLS (KRISTOFERSSON and RICKERTSEN, 2004; STANLEY and JARELL, 2005). In such a case, weighted least squares can be used to derive unbiased and efficient estimates at the second stage.

The assumption of exogenous elastic supply, which is often found in empirical studies applying characteristic models, implies that individuals are price-takers. If individuals are price-takers, the individual's purchase decision does not affect the supply side. This makes it possible to focus solely on the demand side and abstract from any supply-side simultaneous issues. The decision about elastic or inelastic supply is not just important for the specification of the second-stage but also for the first-stage estimation. There are a few papers, amongst others NERLOVE (1995) and RESANO and SANJUÁN (2008), arguing that if consumers are price-takers, they reveal their preferences through the quantities purchased. Consequentially, they estimate the first-stage HPF as a quantity-dependent model. This seems to be a reason-

Figure 2. Different Assumptions about Supply and the Consequences for Estimation which Follow



Source: own presentation

able approach for most retail situations. However, in the case of auction data, consumers reveal their preferences by the price they are willing to pay for the auctioned good, and estimating a price-dependent hedonic model seems to be more appropriate. Accordingly, it seems to be the case that each data set (auction vs. spot market vs. farm level/subsistence) has to be treated differently.

3 Theoretical Model

In this paper, data from spatially and temporarily separated markets, i.e. from different coffee auctions, are used. Following KR (2007), it is assumed that the supply of coffee is fixed at the beginning of each auction resulting in a totally inelastic supply. As coffee is a perennial crop the supplies of characteristics in each auction are predetermined due to planting decisions taken several years before and due to climatic conditions. This implies that the prices of characteristics are solely determined by the quantities of characteristics demanded by coffee importers and roasters. Consequently, the estimation problem is reduced to estimating a non-linear hedonic bid function (HBF) for each market and an inverse characteristic demand function for one characteristic, the sensory quality score (SQS) (see figure 2).

The estimated parameters for each auction are treated as coming from separate markets with identical buyer preferences, i.e. there is no difference in buyer preferences across time and space. This makes it possible to use the within-market variation to identify the marginal characteristic prices and the between-markets variation to identify the inverse demand function for the SQS. The estimated market-clearing HBF is presented by equation (9):

$$(9) \quad b_{in} = \beta_n + \sum_{j=1}^{K} \beta_{jn} z_{jin} + \varepsilon_{in}$$

with b_{in} being the winning bid for coffee i in market n, z_{jin} is the level of characteristic j in coffee i, K is the number of characteristics, β_n and β_{jn} are market-varying parameters to be estimated and ε is a stochastic error term. For each coffee i in the sample, an implicit price for the SQS is calculated from the HBF according to

$$(10) \quad \partial b_{in} / \partial z_{sqs\ in} = \hat{p}_{SQS_{in}} .$$

At the second stage, the inverse demand function for the SQS is estimated according to equation (11):

$$(11) \quad \hat{p}_{SQS_{in}} = \gamma_0 + \sum_{m=1}^{M} \gamma_m x_{inm} + \omega_{SQS_{in}}$$

with $\hat{p}_{SQS_{in}}$ being the estimated marginal price for the SQS of coffee i in market n, x_{inm} are the included explanatory variables with m = 1,..M, γ_o and γ_m represent structural parameters and ω is an error term. To take the problem of unequal accuracy of first-stage estimates into account, the second stage is estimated by weighted least squares, whereas the reciprocal standard errors of the first-stage regression coefficients are used as weights.

4 Data and Empirical Model

The auction data for specialty green coffee beans that have been used cover the time period 2003-2009. Cup of Excellence (COE) competitions and auctions were introduced in Brazil in 1999 to reward high-quality coffee producers and to promote high-quality coffee to consumers. By now, eight Latin American countries, namely Bolivia, Brazil, Colombia, Costa Rica, El Salvador, Guatemala, Honduras and Nicaragua, as well as one African country Rwanda, take part in the COE programme. With the exception of Colombia, where auctions take place twice a year, in all other countries there is usually one auction per year[4]. All data regarding the participating coffee farmers, the coffee characteristics and the closing auction prices are available on the COE website (http://www.cupofexcellence.org). All coffees are cupped in advance by a national and international jury and, based on the cupping experience, each coffee gets a SQS on a scale from 0 to 100 points. Only coffees with a SQS of 84 and above are awarded the COE and are offered in the subsequent internet auctions.

Table 2 presents some descriptive statistics pooled across all data. In total, 1,215 observations from 43 auctions are included. The number of coffee lots sold in an auction varies from 15 to 43 with an average of 28 lots. The average coffee lot size is 2,904 pounds[5]. The price paid for a pound of green coffee beans varies from US-$ 1.3 to US-$ 80.2 with an average of US-$ 5.34. The data set includes 1,620 tonnes of green coffee beans with a total market value of US-$ 17.6 million. The variables denoted as HBF are coffee characteristics included in the estimation of the hedonic bid functions and variables denoted as ID are explanatory variables included in the inverse demand function.

In a first step, hedonic bid functions are estimated by OLS for each auction separately. Non-linear HBF are chosen because in the specialty coffee market unbundling and rearranging different qualities is not possible as these coffees are sold as single-origin coffees. In the mass coffee market this is different, since blending is a standard tool to achieve a certain quality.

The included characteristics are the sensory quality score (*SQS*), the rank achieved in the competition *(rank)*, certification schemes such as organic or fair trade *(certification)* and the available quantity (*quantity*). This leads to the following empirical HBF:

$$\begin{aligned}\log(b_{in}) &= \beta_o + \beta_1 SQS_{in} + \beta_2 rank_{in} \\ &\quad + \beta_3 \log(quantity_{in}) \\ &\quad + \beta_4 certification_{in} + \varepsilon_{in}\end{aligned} \quad (12)$$

The first three ranks are included as dummy variables due to former results on specialty auction coffee highlighting the value of the first three ranks as a marketing tool for consumers (DONNET et al., 2008; TEUBER, 2010).[6] The available coffee quantity is included as a factor of exclusiveness, since it has been shown in hedonic studies on wine that wine produced in limited quantities can achieve higher prices (i.a. COSTANIGRO et al., 2007; SCHAMEL, 2006).[7]

Each HBF is estimated in several functional specifications and each is tested on misspecification using the Ramsey RESET test. The specification fitting the data best is chosen. Furthermore, if heteroscedasticity was detected by the Breusch-Pagan test, the HBFs were estimated with the White Heteroscedasticity consistent estimator.

At the second stage, the following empirical model is estimated:

$$\begin{aligned}\hat{p}_{SQS_{in}} &= \gamma_0 + \gamma_1 \text{average\_score}_\text{n} \\ &\quad + \gamma_2 score\_ratio_{in} + \gamma_4 total\_lots_n \\ &\quad + \gamma_5 trend_n + \gamma_6 CO_n + \gamma_7 buyer_{in} + \varepsilon_n\end{aligned} \quad (13)$$

in which the variables are defined as in table 2. It is assumed that the variable *average_score* has a negative impact on the marginal price, whereas the *score_ratio* is assumed to have a positive impact. The first hypothesis is based on the idea that, if the average quality level

[4] However, there are countries in which auctions do not take place every year. Consequently, there are countries with just one or two observation(s) in the dataset.

[5] Normally, the lot size is given by the number of coffee bags sold. However, since the coffee bag size differs across countries, the average lot size was converted to pounds.

[6] The variables for different certification schemes had to be dropped because of insignificance or too few observations, respectively.

[7] Two anonymous referees raised concerns over the inclusion of quantity as an explanatory variable due to possible endogeneity problems. Endogeneity is of no concern in this setting, since the auction quantity is fixed before the auction bidding starts. However, I did also estimate hedonic price functions excluding the quantity variable in order to check for the robustness of the regression coefficient for the SQS variable. In all cases, the regression coefficient proved to be robust even after dropping the quantity variable.

in terms of the SQS increases, the marginal price of quality will decrease. The second hypothesis implies that relative quality, i.e. the quality of coffee *i* in relation to all other coffees sold in auction *n*, has a positive impact on the marginal price paid for the SQS. We expect a negative impact of the variable *total_lots*, assuming that the larger the auction the less is paid for the SQS. *CO* and *buyer* refer to the geographical

Table 2. Description and Summary Statistics of the Included Variables

Variable	Definition	Mean	Std. Dev.
Dependent variable HBF			
Highest Bid (*high_bid*)	Winning bid for coffee i in US-$/pound	5.34	4.30
Independent variables HBF			
Sensory Quality Score (*SQS*)	The achieved score in the cupping competition that takes place in advance of the auction ranging from 84 -100 points	86.80	2.53
Quantity (*quantity*)	Quantity of coffee i sold in market n in pounds	2651.2	824.5
		Relative Share	
Ranking (*rank*)	Dummy variables for the achieved rank in the cupping competition		
1st Rank	Takes the value 1 if the coffee achieved the 1st rank, and 0 otherwise	0.04	
2nd Rank	Takes the value 1 if the coffee achieved the 2nd rank, and 0 otherwise	0.04	
3rd Rank	Takes the value 1 if the coffee achieved the 3rd rank, and 0 otherwise	0.04	
Rank 4 and lower	Takes the value 1 if the coffee achieved the 4th rank and lower, and 0 otherwise	0.88	
Certification (*certification*)	Dummy variables for different certification schemes		
Organic	Takes the value 1 if the coffee is certified as organic, and 0 otherwise	0.02	
Rainforest Alliance	Takes the value 1 if the coffee is Rainforest-Alliance certified, and 0 otherwise	0.02	
None	Takes the value 1 if the coffee is not certified, and 0 otherwise	0.96	
Dependent variable ID			
Marginal price of the SQS ($\hat{p}_{SQS}$)	Estimated implicit marginal price of the Sensory Quality Score	0.55	0.48
Independent variables ID			
Total number of coffee lots (*total_lots*)	The total number of coffee lots sold in auction n	28.95	6.03
Average score (*average_score*)	The average quality score of all coffees sold in auction n	86.80	0.69
Score Ratio (*score_ratio*)	The score of coffee i in relation to the average score in auction n	1.00	0.03
Time trend (*trend*)	A time trend that takes the value 0 for the year 2003 and the value 6 for the year 2009	3.47	1.86
		Relative Share	
Country-of-Origin (*CO*)	Dummy variables for different coffee origins		
Bolivia	Takes the value 1 if it is a Bolivian coffee, and 0 otherwise	0.05	
Brazil	Takes the value 1 if it is a Brazilian coffee, and 0 otherwise	0.14	
Colombia	Takes the value 1 if it is a Colombian coffee, and 0 otherwise	0.17	
Costa Rica	Takes the value 1 if it is a Costa Rican coffee, and 0 otherwise	0.08	
El Salvador	Takes the value 1 if it is an El Salvadoran coffee, and 0 otherwise	0.17	
Guatemala	Takes the value 1 if it is a Guatemalan coffee, and 0 otherwise	0.07	
Honduras	Takes the value 1 if it is a Honduran coffee, and 0 otherwise	0.09	
Nicaragua	Takes the value 1 if it is a Nicaraguan coffee, and 0 otherwise	0.19	
Rwanda	Takes the value 1 if it is a Rwandan coffee, and 0 otherwise	0.03	
Buying company (*buyer*)	Dummy variable for different buyer origins		
Asian	Takes the value 1 if the coffee was bought by an Asian company, and 0 otherwise	0.52	
European[a]	Takes the value 1 if the coffee was bought by a European company, and 0 otherwise	0.22	
North American	Takes the value 1 if the coffee was bought by a North American company, and 0 otherwise	0.21	
Others	Takes the value 1 if the coffee was bought by a company originating in another country as stated above or a group of companies from different regions, and 0 otherwise	0.05	

[a] European buyer seems to be a rather broad category given the differences between Northern and Southern European countries in terms of their coffee consumption patterns. However, since there are only very few buyers from Southern Europe in the data set, a more disaggregated examination was not feasible.
Source: own presentation

origin of the coffee and bidding company, respectively. We distinguish between Asian, European and North American companies, assuming that consumers' preferences may differ across these market segments. At first glance, the inclusion of this variable may seem puzzling given the statement above that we assume identical buyer preferences across time and space. However, this approach is fully in line with the theoretical model, since identical buyer preferences refer to each buyer category across different auctions. This means that we expect a European buyer to exhibit the same preferences across all the included auctions but we do not assume that European and Asian buyers possess identical preferences.

5 Results

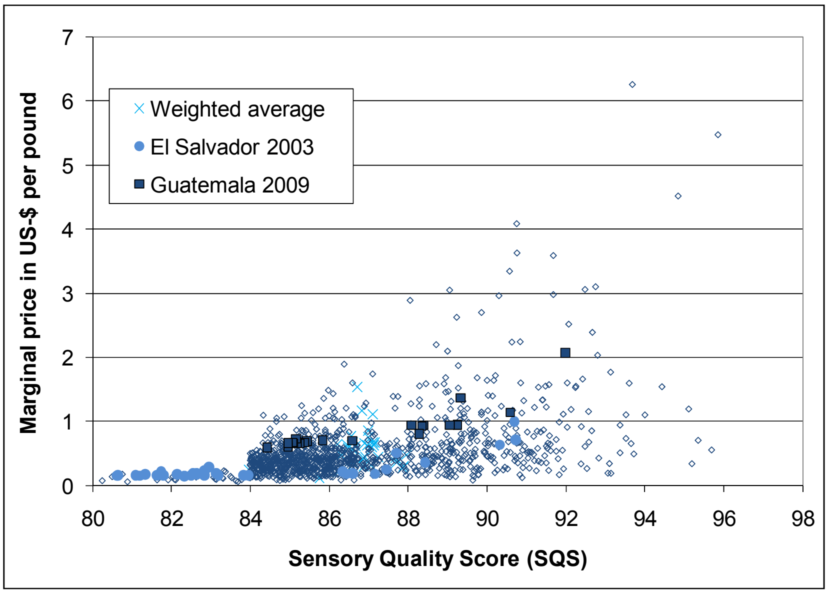
In all cases, the HBF is estimated in a log-linear specification as presented in equation (12). This means that the marginal price of the SQS has to be calculated as:

(14) $\hat{p}_{SQS_{in}} = \beta_1 * b_{in}$

with b_{in} being the winning bid of coffee i in auction n.

Figure 3 illustrates the high variability of the marginal price of the SQS across different auctions by depicting all estimated marginal prices as well as the marginal prices calculated at the weighted mean price achieved in auction n in absolute terms.[8]

Figure 3. Marginal Pricing Schedule from First-Stage Hedonic Bid Functions in Absolute Terms



Source: own calculations

If we just look at the marginal prices calculated at the weighted average, there seems to be no clear pattern in terms of an increasing or falling marginal price according to the level of the SQS. This is different, if we look at the dispersion of marginal prices within an auction. Marginal prices for two different auctions, namely Guatemala 2009 and El Salvador 2003, are highlighted in order to illustrate the increasing marginal pricing schedule. Moreover, these highlighted marginal prices also stress the existing level differences between auctions. This is in line with findings from previous hedonic studies on the specialty coffee market, stressing the importance of region and time dummies in pooled hedonic regressions (DONNET et al., 2008; TEUBER, 2009).

One example of an HBF based on data for the year 2008 is presented in table 3. The estimated parameters of three different model specifications based on pooled data across all auctions that took place in the year 2008 are presented in the first three columns. The last column contains estimated regression coefficients for the SQS from the HBF estimated using data from individual auctions. Consequently, regression coefficients for the other variables are not reported. The model specification presented in the second column allows the price level to differ across countries but assumes a constant regression coefficient for the SQS. The model specification in the third column introduces flexibility by allowing the impact of the SQS to differ across countries, whereas all other explanatory variables are assumed to have the same impact across countries.

All estimated coefficients exhibit the expected signs. The SQS and the first three ranks affect the achieved auction price positively, whereas the quantity has a negative impact. The regression coefficient for the SQS in the country-effects model is the average impact across all the included auctions, i.e. across countries. This parameter indicates that an increase in the SQS by one unit results in price increasing by 11%. The same parameter is obtained when we calculate the average across all individual country regression coefficients presented in the last column of table 3.

The results with respect to price level differences between countries are surprising. Honduras was chosen as the reference category, since

[8] The weights are sold quantities.

Table 3. Parameter Estimates of the Hedonic Bid Function, Auction Year 2008

	Model 1: Basic Model	Model 2: Basic Model with CO Effects	Model 3: Basic Model with CO and Interaction Effects (CO * Score)	Score Parameter Estimates from Individual HBFs
Dependent variable Log(High_bid)				
Constant	-5.28*** (0.000)	-5.00*** (0.000)	-11.24*** (0.000)	
SQS	**0.115*** ** (0.000)	**0.110*** ** (0.000)	**0.179*** ** (0.000)	
Ranking (Reference: Rank 4 and lower)				
1st Rank	0.521** (0.003)	0.527*** (0.000)	0.542*** (0.000)	
2nd Rank	0.305** (0.009)	0.305** (0.007)	0.307*** (0.000)	
3rd Rank	0.240 (0.064)	0.232* (0.042)	0.213* (0.011)	
Log(*quantity*)[a]	-0.367*** (0.000)	-0.353*** (0.000)	-0.318*** (0.000)	
CO Effect (Reference: Honduras)				
Bolivia		-0.167** (0.006)	-0.171** (0.003)	
Brazil		-0.018 (0.805)	-0.011 (0.834)	
Costa Rica		-0.167* (0.010)	-0.176** (0.003)	
Colombia		0.154* (0.027)	0.212*** (0.000)	
El Salvador		-0.126* (0.032)	-0.138* (0.013)	
Guatemala		0.325*** (0.000)	0.328*** (0.000)	
Nicaragua		-0.087 (0.206)	-0.097 (0.135)	
Rwanda		0.099 (0.138)	0.092 (0.143)	
Interaction Effects CO * Score (Reference: Honduras*SQS)				
Honduras*SQS				0.214*** (0.000)
Bolivia*SQS			-0.079** (0.003)	0.125*** (0.000)
Brazil*SQS			-0.148*** (0.000)	0.063*** (0.000)
Costa Rica*SQS			-0.036 (0.272)	0.109** (0.002)
Colombia*SQS			-0.140*** (0.000)	0.057*** (0.000)
El Salvador*SQS			-0.070* (0.011)	0.123*** (0.000)
Guatemala*SQS			-0.020 (0.625)	0.078* (0.038)
Nicaragua*SQS			-0.067* (0.034)	0.089 (0.077)
Rwanda*SQS			-0.064* (0.039)	0.140** (0.005)
Adjusted R^2	**0.64**	**0.76**	**0.80**	-
RESET statistic	**1.80 (0.18)**	**6.18 (0.01)**	**24.39 (0.00)**	-
N	**236**			

Notes: p-values are presented in parentheses; *, **, *** denote significance at the 5%, 1% and 0.1% level, respectively.
Source: own estimations

in former studies its coffees were sold at a discount compared to other origins *ceteris paribus*[9]. This is not the case in the auction year 2008, in which only Colombian and Guatemalan coffees were sold at a significantly higher price level, looking at the main *CO* effects in Model 2. These main *CO* effects change only slightly if interaction effects (CO*SQS) are included (Model 3). In five cases out of eight, the main CO effects are statistically significant different from zero. Coffees from Bolivia, Costa Rica and El Salvador are sold at a lower price level than Honduran coffees, whereas Colombian and Guatemalan coffees can achieve higher prices, holding all other variables constant. However, our main interest concerns the conditional score effects. Six out of eight interaction effects are negative at a statistically significant level, implying that the score is less valued for coffees from Bolivia, Brazil, Colombia, El Salvador, Nicaragua and Rwanda compared with coffee from Honduras. Hence, adding interaction effects highlights that the SQS does not have the same impact on the auction price achieved across countries. In the case of Honduran coffee, a one-unit increase in the score results in an 18.1% higher auction price. In contrast, a one-unit increase in the score of a Brazilian coffee induces a price increase of 3.3% only.[10]

9 This is also the case if a HBF is estimated based on the whole data set. These results are not reported due to space limitations.

10 This is calculated by subtracting the estimated parameter for Brazil*score from the reference score regression coefficient, i.e. [0.181-0.148].

If we compare the estimated regression coefficients from the cross-section model with the parameter estimates for the score variable from separately estimated HBFs, the tendency in both cases is the same, i.e. the highest estimated coefficient is that of Honduras and the lowest ones are found for Brazil and Colombia. However, since not all possible interaction effects are included in the pooled model presented in the third column, the estimates are not identical. For the inverse demand model at the second stage, first-stage parameters from individually estimated HBFs are used. The second stage is estimated both by ordinary and weighted least squares. In the latter case, the inverse standard errors from the first-stage estimates are used as weights. This means that more precise estimates are given more weight than less precise ones. Moreover, several functional specifications were tested and the double-log models performed best. The results for both estimation procedures are presented in table 4.

Despite the results for the variable *total_lots*, the OLS and WLS estimates are consistent in terms of the direction of the impact. For some variables such as *average_score* and several *CO* dummies the magnitude of the impact differs. As expected, the WLS estimates are more efficient than the ones derived by OLS and will be interpreted and discussed below.

Table 4. Parameter Estimates of the Inverse Demand Function for the SQS

	OLS		WLS[a]	
Variable	**Parameter estimate**	**p-value**	**Parameter estimate**	**p-value**
Dependent variable: log($\hat{p}_{SQS_{in}}$)				
Constant	15.067*	0.048	69.329***	0.000
Log(total_lots)	0.263***	0.000	-0.153*	0.046
Log(average_score)	-6.385***	0.000	-18.405***	0.000
Score_ratio	10.99***	0.000	11.987***	0.000
Trend	0.244***	0.000	0.234***	0.000
CO Effects (*Reference: Honduras*)				
Bolivia	0.019	0.709	-0.231***	0.000
Brazil	-0.064	0.064	-0.222**	0.000
Colombia	-0.204***	0.000	-0.258**	0.000
Costa Rica	-0.567***	0.000	-0.685***	0.000
El Salvador	-0.357***	0.000	-0.567***	0.000
Guatemala	-0.123*	0.029	-0.374***	0.000
Nicaragua	-0.194***	0.000	-0.224***	0.000
Rwanda	0.368***	0.000	0.150*	0.000
Buyer (*Reference: North American*)				
Asian	-0.136***	0.000	-0.156***	0.000
European	-0.046	0.220	-0.032	0.492
Others	0.128*	0.050	0.082	0.284
Adjusted R^2	**0.67**		**0.73**	
RESET statistic (p-value)	**2.36 (0.12)**		**3.64 (0.06)**	
N	**1216**			

[a] Weights are equal to the inverse standard errors of the regression coefficients from the first stage. *, **, *** denote significance at the 5%, 1% and 0.1% level, respectively. Test statistics are based on White's corrected standard errors.
Source: own estimation

The impact of the variables *total_lots*, *average_score* and *score_ratio* confirm our hypotheses. If the number of coffee lots sold in auction *n* increases, the marginal price for the SQS decreases. The same negative relationship is true for the average score achieved in auction *n*. If the average score increases by 1%, the marginal price of the SQS decreases by 18%. In contrast, an increasing *score_ratio* leads to an increase in the marginal price of the SQS. This finding is fully in line with the increasing marginal price schedule presented in figure 3. As indicated by the positive time trend, marginal prices of the SQS have increased over time due to the increasing price level in these auctions.

The implicit price paid for a one-unit increase in the SQS is highest for Rwandan and Honduran coffee. This is reflected in the significantly negative coefficients for all other *CO* dummies. At first glance, this seems to contradict first-stage findings from previous studies, where Honduran coffees are discounted to the price level of all other origins (DONNET et al., 2008; TEUBER, 2010). However, looked at more closely, these results might even explain the findings presented here. Since Honduras does not yet possess a well-established reputation as a high-quality producer, the SQS seems to be a more important product characteristic than for coffees from other origins which sell "by themselves" due to their established image. The results suggest that the same is true for coffee from Rwanda. However, since only one auction has taken place in Rwanda so far, these results have to be interpreted with caution.

Another interesting finding refers to the impact of the *buyer* variable. No statistically significant differences could be detected between North American, European and other buyers. On the contrary, there is a statistically significant negative impact on the marginal price of the SQS by the Asian buyer variable. A possible explanation may be that Asian consumers rely more on other product characteristics such as regional reputation or ranking and the

SQS is, therefore, not valued as highly as by buyers from other consumer markets. This raises the question whether distinct consumer segments exist in the specialty coffee market, in which product characteristics are valued differentially. This seems to be an interesting issue for future research.

6 Concluding Remarks

It is known that estimating demand and supply functions in the characteristics space is quite distinct from the goods space. Although the theoretical basis of two-stage hedonic models is sound, empirical applications are not straightforward. Data requirements are demanding and, depending on the type of data used, several estimation problems have to be tackled. Given the increasing availability of comprehensive electronic data sets, the number of studies estimating two-stage hedonic models will certainly increase.

The present paper has used a data set on specialty coffee to estimate a two-stage hedonic model. First-stage marginal prices were estimated for the sensory quality score achieved for each auction, and these marginal prices were then used as dependent variables in an inverse demand model. The first-stage results indicate that marginal prices differ significantly across auctions and that a pooled HBF can only provide a complete picture if all possible interaction terms are incorporated. The second-stage results highlight the fact that marginal prices of the SQS increased from 2003 to 2009 and differed significantly across growing and buyer origins. Surprisingly, the country-of-origin effects are different between the goods and the characteristics space. In the first instance, Honduran coffee was usually discounted to all other origins, whereas Guatemalan and Colombian coffees have achieved the highest prices. This is not the case if we look at the second-stage results. In the characteristics space, the marginal price paid for the SQS is significantly higher for Honduran and Rwandan coffees than for any other origin. This can possibly be due to the lack of reputation of these two exporters. The SQS seems to be a much more important quality cue for these coffees than for coffees originating in coffee-growing countries with a well-established reputation.

Although the present empirical analysis offers some interesting results, it has several limitations. First, only very few characteristics could be included because of a lack of detailed data or a missing variance in the data set. Therefore, no substitutive or complementary relationships, for example attribute trade-offs, could be modelled. Second, the data set used includes only a small portion of the whole specialty coffee market. In order to overcome these limitations, it seems fruitful in future research to utilize more comprehensive data sets as they become available.

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RAMONA TEUBER
Justus Liebig University Giessen
Institute of Agricultural Policy and Market Research
Senckenbergstr. 3, 35390 Giessen, Germany
e-mail: Ramona.Teuber@agrar.uni-giessen.de

Annex

Annex 1. Included Auctions in the Two-Stage Hedonic Model

Country	Included auction years (*number of coffees sold*)
Bolivia	2004 *(13);* 2005 *(29);* 2007 *(26);* 2008 *(29)*
Brazil	2003 *(43)*; 2004 (36); 2005 *(36);* 2006 *(29)*; 2008 *(23)*
Colombia	2005 *(33, 25);* 2006 (30, 23); 2007 (30); 2008 (18); 2009 (27)
Costa Rica	2007 *(25)*; 2008 *(30);* 2009 *(24)*
El Salvador	2003 *(31);* 2004 *(35);* 2005 *(17);* 2006 *(23);* 2007 *(23);* 2008 *(36);* 2009 *(33)*
Guatemala	2006 *(25);* 2007 *(19);* 2008 *(25);* 2009 *(23)*
Honduras	2004 *(21);* 2005 *(41);* 2006 *(33);* 2007 *(24);* 2008 *(26)*
Nicaragua	2003 *(37);* 2004 *(29);* 2005 *(35);* 2006 *(25);* 2007 *(34);* 2008 *(25)*
Rwanda	2008 *(24)*

Source: own presentation