European Review of Agricultural Economics pp. 1–30
doi:10.1093/erae/jby024

Credence attributes and the quest for a higher price – a hedonic stochastic frontier approach

Alessandro Bonanno[†,‡], Francesco Bimbo[*,§,††], Marco Costanigro[†], Alfons Oude Lansink[§] and Rosaria Viscecchia[††]

[†]*Colorado State University, USA;* [‡]*The Pennsylvania State University, USA;* [§]*Wageningen University, The Netherlands;* [††]*Università degli Studi di Foggia, Italy*

Received March 2017; editorial decision April 2018; final version accepted June 2018

Review coordinated by Giannis Karagiannis

Abstract

Food manufacturers that offer credence attributes, whose presence cannot be determined a priori, may fail to differentiate their products effectively and achieve higher prices if asymmetric information (on the producers' side) impairs their ability to reach consumers with higher willingness to pay. In this article, we assess whether manufacturers carrying products with credence attributes in their portfolio are able to obtain higher prices. To this end, we use a large database of yoghurt sales in Italy and a hedonic price model estimated using a stochastic frontier estimator. The results indicate that manufacturers that offer more credence attributes in their portfolios have the ability to price their products systematically at higher levels.

Keywords: hedonic price model, credence attributes, stochastic price frontier

JEL classification: Q11, Q13, I12

1. Introduction

Price dispersion occurs when the price of identical goods varies across suppliers and markets. The rationale for the existence of price dispersion has been explored at length in the economics literature: following the seminal work by Stigler (1961), several frameworks (*inter alia* Salop, 1977; Salop and Stiglitz, 1977, 1982; Burdett and Judd, 1983) showed that if information

*Corresponding author: E-mail: francesco.bimbo@unifg.it; francesco.bimbo@wur.nl

gathering is costly for consumers, asymmetric information may enable suppliers to price discriminate and more than one price equilibrium will emerge.[1] Even though these theories were developed for homogenous product markets, a similar counterpart exists for differentiated product markets (e.g. Barron, Taylor and Umbeck, 2004; Lewis, 2008), where 'local' competition and consumer search cost can lead to variation in differentiated products' prices even after differences in consumers' willingness to pay (WTP) for specific products are controlled for. In fact, information costliness can lead to systematic differences in price charged to consumers in differentiated product markets: Wildenbeest (2011), extending Armstrong and Vickers' (2001) model of consumers search in a market with vertically differentiated products, shows that if information is costly, some firms are able to charge systematically higher prices than their competitors.

Many differentiated food products can be characterised as credence goods – that is, goods that carry credence attributes (i.e. 'organic' or 'natural' labels, health claims, GMO-free etc.) whose quality level cannot be detected by consumers even after consumption (Nelson, 1970; Darby and Karni, 1973). Since quality signalling cannot be substantiated by consumers' experience, firms may struggle to develop reputations for credence quality traits, and consumers' heterogeneous beliefs about quality provision may lead to price dispersion. However, in the presence of third-party certifications and labelling regulations, asymmetric information can be reduced (e.g. Caswell and Padberg, 1992; Caswell and Mojduszka, 1996; Teisl and Roe, 1998) and, if the certification is probabilistically accurate,[2] credence goods markets can become experience goods markets (McCluskey, 2000) and effective signalling can occur.

Suppliers' reputation may also come into play allowing sellers to systematically target consumers with higher WTP for products with similar features to their competitors'.[3] A strong link exists between the strength of a brand and the effectiveness of quality signalling, particularly in the context of credence attributes (Sporleder and Goldsmith, 2001). Some research indicates that

1 Non-unique price equilibria can be sustained by numerous factors: asymmetric information (sellers have information on buyers' behaviour and their reservation price), variation in product quality and consumers' heterogeneity. Empirical applications studying price dispersion for homogenous products abound: Devine and Marion's (1979) first empirical study of price dispersion in retail food prices in function of information; Borenstein and Rose's (1994) analysis of competition in airline price dispersion; Sorensen's (2000) study of price dispersion in the retail prescription drug market; Lach's (2002) assessment of long-term price dispersion in retail prices of homogenous food products; Zhao's (2006) investigation of intra-brand, intra-store and intra-category price dispersion in several food and non-food grocery categories and Richards, Hamilton and Allender's (2016) study of search cost and price dispersion in a UK online grocery.

2 Bonroy and Constantatos (2008) show that if consumers' beliefs regarding the firm selling the high-quality product are idiosyncratic, labels that restore full information improve welfare but cause a decline in firms' profits and that imperfect labels can have adverse welfare effects. For a thorough discussion of the economics of labels and their effect on welfare, see Bonroy and Constantatos (2015).

3 See Saitone and Sexton (2017) for a detailed discussion of the recent trends in consumer demand for credence attributes in food products and the complex implications of the coexistence of multiple credence attributes for the performance of agri-food supply chains.

signalling higher quality to consumers through credence attributes may lead to brand loyalty (e.g. Lassoued and Hobbs, 2015), whereas others (Bimbo, Bonanno and Viscecchia, 2016) show that brand strength is linked to obtaining higher premiums for some types of health claims in the Italian yoghurt market. Furthermore, brand strength is considered a quality signal in the wine market, where both collective and private reputation can contribute to higher prices (e.g. Costanigro, McCluskey and Goemans, 2010). This would indicate that, at least potentially, a manufacturer carrying credence goods in its portfolio could benefit from improved brand image/reputation and improve its ability to target high-WTP consumers.[4] Adding products with credence attributes to their portfolio may also improve manufacturers' ability to charge higher prices through mechanisms other than reputation. Similarly, some studies suggest that product-line length[5] can serve as a quality cue for consumers (Bergen, Draganska and Simonson, 2007), increasing consumers' brand loyalty and ultimately allowing producers to charge higher prices (Draganska and Jain, 2005).

The central question addressed in this article pertains to whether credence labelling helps manufacturers to achieve higher prices or whether the presence of asymmetric information and consumer distrust hinders such ability. In other words, we seek answers to the question: do manufacturers adding products with credence attributes to their portfolio systematically reach consumers with higher WTP? Answering this research question requires testing empirically whether the presence of products with credence attributes in a manufacturer's portfolio is related to the price of the different products sold once other sources of price variation are controlled for, such as individual product characteristics, including the credence attributes themselves, brands (which may embed 'reputation' through other avenues, such as advertising etc.) and temporal and geographical variation.

An intuitively appealing framework for answering this question is the hedonic price model (Rosen, 1974), which maps a product price to the value of each embedded attribute (Lancaster, 1966) by tracing the envelope of the bid functions representing consumers' WTP for the different attributes and the offer functions representing producers' technological constraints. However, the traditional hedonic price model is insufficient for addressing our problem for two reasons. First, in a traditional hedonic price model, reputation effects are measured by estimating the implicit prices associated with specific labelling/brand attributes, affecting prices in an additive way (e.g. Costanigro, McCluskey and Goemans, 2010). We posit instead that increasing the number of credence attributes has a systematic effect on the shape of the entire hedonic price curve, and therefore we need to test for the existence

4 For example, the literature summarised in Bimbo *et al.* (2017) shows that consumers with low interest in health show higher preference for and acceptance of 'health-enhancing' dairy products if they are offered by brands familiar to the consumers.

5 'Product-line length' refers to the total number of product options or unique combinations of product features (e.g. type of flavour, fat content, consistency, health benefit) sold by a manufacturer.

of supra-additive effects. Second, the traditional hedonic price framework assumes that buyers and sellers are fully informed – that is, every seller knows consumers' highest WTP, and every buyer knows the sellers' lowest willingness to accept (WTA), which is not the case of markets with credence attributes. Recently, Kumbhakar and Parmeter (2010) extended Rosen's framework to allow sellers' and buyers' characteristics to affect the shape of the hedonic price function, while at the same time relaxing the full information assumption and allowing for the coexistence of multiple hedonic functions, which depend upon the level of information that buyers and sellers possess. Kumbhakar and Parmeter (2010) model a portion of the unobservable price variation as a function of sellers' (buyers') features to capture the extent of information asymmetry that may prevent sellers (buyers) from fully exploiting the highest (lowest) values of buyers' WTP (sellers' WTA) for a bundle of attributes available in a market, generating multiple price equilibria.

In this article, we use Kumbhakar and Parmeter's (2010) modified hedonic price framework to test whether manufacturers investing in credence attributes are able to effectively signal product quality and to price their products closer to the hedonic price curve characterised by consumers with the highest WTP. Thus, we assume a scenario where fully informed producers face imperfectly informed consumers and test whether manufacturers carrying a larger number of credence attributes are able to reach consumers with a higher WTP for their products. We estimate this 'buyer's price frontier' (as defined by Kumbhakar and Parmeter, 2010) by means of a stochastic frontier (SF) estimator, which represents a novel approach in the context of the application of hedonic price modelling to differentiated food products.[6] For our empirical application, we choose the Italian yoghurt market and focus on a 2-year scanner database of monthly yoghurt sales at the regional level. We use different model specifications and variables to capture the number of credence attributes in each manufacturer's portfolio. We assume that the number of credence attributes affects the dispersion of manufacturers' prices below the hedonic price curve; given our hypothesis that firms using more credence attributes will charge (*ceteris paribus*) higher prices, we expect that the more credence attributes are offered, the less dispersed (i.e. the closer to the buyer's price frontier) a firm's prices will be.

We choose the Italian yoghurt market as a case study for different reasons. In general terms, the yoghurt category is a fitting case study due to the high product heterogeneity and its oligopolistic nature (e.g. Villas-Boas, 2007; Bonanno, 2013; Hovhannisyan and Bozic, 2013), which makes it an ideal candidate to test for the coexistence of different prices. Furthermore, Italian yoghurt manufacturers have used different credence attributes to differentiate

6 SF instead has been widely adopted to account for the sources of price heterogeneity in the housing market (e.g. Kumbhakar and Parmeter, 2010; Carriazo, Ready and Shortle, 2013), lumber market (Kalita, Jagpal and Lehmann, 2004), consumer electronics market (Lee *et al.*, 2008) and online airline ticket market (Kamakura and Moon, 2009).

their products, from 'organic' and 'natural' to a series of different health claims (Bonanno, 2012). Given the marked heterogeneity of the products in this market, it is possible for different types of consumers to have different attitudes towards them. For example, even though asymmetric information may cause consumers to distrust products carrying health claims (e.g. Verbeke, 2005a, 2005b), resulting in some consumers' low WTP for products carrying these attributes, the presence of health claims in European markets has been subjected to a tight regulatory framework, the Reg. (EC) No.1924/2006.[7] Therefore, although on the one hand, the stringency of the regulation may add to manufacturers' uncertainty about the profitability of their investment (e.g. Brookes, 2010), which may result in not all Italian yoghurt manufacturers being able to use health claims as a means of product differentiation (e.g. Bimbo, Bonanno and Viscecchia, 2016), on the other hand, the high-quality standard may be preferred by consumers with higher WTP and enable Italian yoghurt manufacturers to exert higher prices.

The article proceeds as follows. First, we present the empirical framework of our analysis, followed by a discussion of our model specification, the data used and the details of the estimation procedure adopted. Next, the empirical results will be presented and discussed. We conclude with a discussion of the limitations of the current work and avenues of future research.

2. The empirical framework

Our empirical framework starts from the traditional hedonic price model formalised by Rosen (1974). According to this framework, consumers choose products that contain a utility-maximising bundle of attributes, subject to a budget constraint. Producers choose a profit-maximising combination of attributes subject to the available technology embedded in the cost function. The first-order conditions of each maximisation problem lead to two families of indifference curves, which have product attributes as their arguments: the consumers' bid and producers' offer functions. The *bid function* $\theta = \theta(x_1, x_2, \ldots, x_k; u, y)$ represents the amount a consumer is willingness to pay (WTP) for varying levels of the attribute vector $\mathbf{x} = (x_1, x_2, \ldots, x_k)$, holding utility, u and income, y, constants. Analogous to the consumer's bid function, the seller's *offer function* $\varphi = \varphi(x_1, x_2, \ldots, x_k; \pi)$ indicates the price that a firm is willing to accept for selling a good with the characteristics vector $\mathbf{x}$ while maintaining the (fixed) profit π. Under the assumptions of perfect competition and full information, the double envelope traced by the points of tangency between bid and offer curves results in the hedonic price function $p(\mathbf{x}) = p(x_1, x_2, \ldots, x_k)$,

7 The European Union's Regulation (EC) No.1924/2006 aims to reduce asymmetric information in food products markets and to guarantee that nutrition and health claims are truthful and understandable. Claims falling under article 13 are divided into 'general function' claims (Article 13.1) and general function claims based on new and/or proprietary data (Article 13.5). Claims falling under Article 14, i.e. 'risk reduction' claims deal with risk factor reduction in the development of a human disease. Research shows that 'risk reduction' claims have higher market valuation than 'general function' claims (i.e. Bimbo, Bonanno and Viscecchia, 2016).

establishing a unique price conditional on $p^{\circ}(\mathbf{x})$; in Figure 1, the two matched sets of bid/offer curves are labelled with the superscripts 1 and 2.

According to Rosen's model, the observed price of a product j in market m at time t is a function of product attributes, plus an error term accounting for random shocks and unexplained product heterogeneity:

$$P_{jmt} = f(\mathbf{x}_{jmt}, \boldsymbol{\beta}) + \varepsilon_{jmt} \tag{1}$$

where the functional form $f(\bullet)$ is to be determined empirically and $\boldsymbol{\beta}$ is a conforming vector of the parameters to be estimated (Costanigro and McCluskey, 2011).

Kumbhakar and Parmeter (2010) modify the classical hedonic framework to relax the full information assumption, allowing for multiple price equilibria to coexist when information is imperfect or asymmetric. In their model, consumers with the highest WTP for a certain attribute level identify the upper boundaries of the attainable market prices $p^{\mathrm{HIGH}}(\mathbf{x})$ (*buyer's price frontier*), while producers with the lowest WTA trace the lower bounds $p^{\mathrm{LOW}}(\mathbf{x})$ (*seller's price frontier*), as shown in the middle panel of Figure 1. Lacking full information, transactions can occur anywhere in-between the two lines, with the two polar cases of fully informed producers matched to information-deficient consumers (offer and bid curves, respectively, carrying the superscripts 3 and 4) or fully informed buyers matched with information-deficient sellers (offer and bid curves, respectively, showing superscripts 5 and 6). Our analysis investigates the case of fully informed producers and imperfectly informed consumers; that is, we focus on the ability of manufacturers to reach $p^{\mathrm{HIGH}}(\mathbf{x})$, depicted in the right-hand panel of Figure 1.

Thus, equation (1), which treats the error term as a nuisance parameter, is insufficient for modelling systematic departures from the hedonic price function. Following Kumbhakar and Parmeter (2010), we account for buyers with the highest WTPs or sellers with the lowest WTAs by separating the error term in equation (1) into three components:

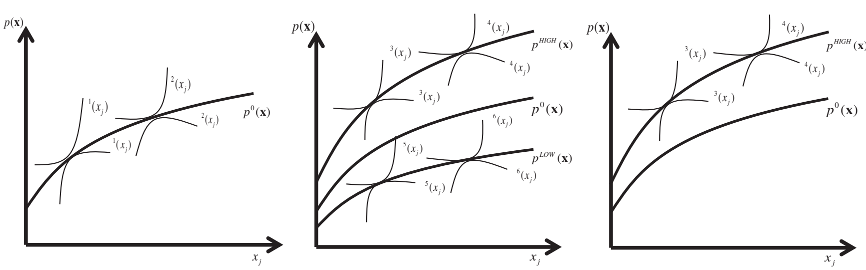

Fig. 1. Graphical representation of equilibrium prices and hedonic price curves. Left panel: traditional hedonic price model; middle graph panel: model with imperfectly informed consumers and producers (adapted from Kumbhakar and Parmeter, 2009); right panel: model with incompletely informed consumers.

$$P_{jmt} = f(\mathbf{x}_{jmt}, \boldsymbol{\beta}) + \varepsilon_{jmt} = f(\mathbf{x}_{jmt}, \boldsymbol{\beta}) + v_{jmt} + w_{jmt} - u_{jmt} \tag{2}$$

Equation (2) shows that the unobserved portion of the price of product j in market m at time t is constituted of v, a random noise component, and u and w, which are two one-sided (half-positive) errors. The term w ($w \geq 0$) represents the cost incurred by consumers for not being fully informed and/or for not being able to assess the 'true' value of a given product. The term u instead ($u \geq 0$) is the loss that a seller may incur for not being able to target those consumers with the highest WTP for a product containing a given bundle of attributes. Thus, in a market characterised by asymmetric information, the random term ε embodies two different measures of *price inefficiencies*, one from the consumers' standpoint (w) and another from the producer's (u). Note that under such specification, $E(\varepsilon)$ may be non-zero, even when $E(v) = 0$. In the presence of either inefficiencies on both sides (Kumbhakar and Parmeter, 2010) or on one side of the market only (e.g. Kamakura and Moon, 2009; Carriazo, Ready and Shortle, 2013), the structure of the one-sided errors should be appropriately specified.

As illustrated above, in this application we assume $w = 0$ and parameterise the variance of the one-sided error u, σ_u^2 to capture the determinants of manufacturer's inability to reach consumers with the highest WTP. Following previous literature (e.g. Carriazo, Ready and Shortle, 2013), the following specification of the variance of the error u is assumed:

$$\sigma_u^2 = \exp(\boldsymbol{\lambda}'\mathbf{z}) \tag{3}$$

where the vector $\mathbf{z}$ contains variables affecting the ability of manufacturers to charge prices closer to the buyer's price frontier (illustrated below) and $\boldsymbol{\lambda}$ is a conformable vector of parameters.

3. Model specification, data and estimation

3.1. Model specification

For our specification of equation (2), $\mathbf{x}$ is partitioned into five vectors, i.e. $\mathbf{x}^{\mathbf{CA}}$, $\mathbf{x}^{\mathbf{NOC}}$, $\mathbf{x}^{\boldsymbol{P}}$, $\mathbf{x}^{\boldsymbol{R}}$ and $\mathbf{x}^{\boldsymbol{B}}$ (product, market and time subscripts are omitted for brevity). $\mathbf{x}^{\mathbf{CA}}$ represents a vector of product characteristics capturing credence attributes (CA) indexed by h ($h = 1,\ldots,H$); $\mathbf{x}^{\mathbf{NOC}}$ includes non-credence (NOC) product characteristics, indexed by l ($l = 1,\ldots,L$). $\mathbf{x}^{\boldsymbol{P}}$ and $\mathbf{x}^{\boldsymbol{R}}$ include package and retail characteristics and are indexed by ($p = 1,..,P$) and ($r = 1,..,R$), respectively. Last, $\mathbf{x}^{\boldsymbol{B}}$ is a vector of brand-specific indicator variables indexed by b ($b = 1,\ldots,B$).

Following previous literature (*inter alia* Costanigro, McCluskey and Mittelhammer, 2007; Costanigro, McCluskey and Goemans, 2010; Bimbo, Bonanno and Viscecchia, 2016; Waldrop, McCluskey and Mittelhammer, 2017), we focus only on the first stage of the hedonic model (i.e. we do not recover marginal WTP for the attributes). For our empirical specification of equation (1), we choose a Box–Cox functional form, which previous research shows to outperform other widely used functional forms (such as linear and log-linear) in terms of limiting omitted variables bias (e.g. Kuminoff, Parmeter and Pope, 2010):

$$P^{\tau}_{jmt} = \alpha + \sum_{h=1}^{H} \alpha_h x^{\mathrm{CA}}_{hmt} + \sum_{l=1}^{L} \beta_l x^{\mathrm{NOC}}_{lmt} + \sum_{p=1}^{P} \delta_p x^{P}_{pmt} + \sum_{r=1}^{R} \gamma_r x^{R}_{rmt} + \sum_{b=1}^{B} \kappa_b x^{B}_{bmt} + \sum_{m=1}^{M} \theta^{M}_{m} d_m + \sum_{t=1}^{T} \theta^{T}_{t} d_t + \varepsilon_{jmt} \tag{4}$$

where the exponent τ is to be determined empirically, and spatial- and time-specific variation in prices are controlled for by means of a vector of M market-level (region) and T time (month) indicators, d_{m} and d_{t}, respectively, included in the model to reduce the risk of omitted variable bias that may arise when panel data are used (e.g. Kuminoff, Parmeter and Pope, 2010). The α_{s}, β_{s}, δ_{s}, γ_{s} and κ_{s} are parameters to be estimated capturing, respectively, the market valuation of credence attributes, non-credence attributes, packaging and retail-specific variables and brands, and ε_{jmt} is an error term whose properties are discussed above. In the robustness checks section, we use alternative functional forms of equation (4).[8]

We use eight different specifications of equation (3) to parametrise the variance of the inefficiency term u. The first four specifications are:

$$\sigma^2_u = \exp\left(\lambda_0 + \sum_{k=1}^{4} \lambda^{\mathrm{HC}}_k \mathrm{HC}_k\right); \tag{5a}$$

$$\sigma^2_u = \exp\left(\lambda_0 + \sum_{i=1}^{4} \lambda^{\mathrm{CR}}_i \mathrm{CR}_i\right); \tag{5b}$$

$$\sigma^2_u = \exp(\lambda_0 + \lambda^{\mathrm{NHC}}\mathrm{NHC} + \lambda^{\mathrm{NHCItems}}\mathrm{NHC} * \mathrm{Items}); \tag{5c}$$

$$\sigma^2_u = \exp(\lambda_0 + \lambda^{\mathrm{NCR}}\mathrm{NCR} + \lambda^{\mathrm{NCRItems}}\mathrm{NCR} * \mathrm{Items}). \tag{5d}$$

where HC_k is an indicator variable capturing whether a manufacturer has in its portfolio a given number of products with functional/health claims $\{k = 1,\ldots,4\}$, CR_i is an indicator variable capturing whether a manufacturer produces a given number of products with credence attributes $\{i = 1,\ldots,4\}$, NCR is a variable capturing the number of different credence attributes offered by a manufacturer in its portfolio, NHC takes values equal to the number of functional/health claims in a manufacturer's portfolio; last, *Items* is the average number of product items sold in stores. This last variable may

8 Additionally, we estimated our hedonic price model using a log-linear functional form and calculated 'price-efficiency' values, as suggested by an anonymous reviewer.

be indirectly related to a producer's product-line length as well as to its market image, however, it is largely under the control of the retailer.

Our hypothesis is that by offering a larger number of credence attributes, manufacturers can increase their ability to price their products closer to the buyer's price frontier; thus, we expect σ_u^2 to decline with the number of credence attributes produced. In other words, for specification (5a) and (5b), we expect (1) the signs of the parameters λ_i^{CR} and λ_k^{HC} to be negative and (2) that $|\lambda_i^{CR}| < |\lambda_{i+1}^{CR}|$ and $|\lambda_k^{HC}| < |\lambda_{k+1}^{HC}|$ for $i = \{1,\ldots, 3\}$ and $k = \{1,\ldots, 3\}$. If these conditions are met, they will provide empirical support to the hypothesis that manufacturers that produce more products with credence attributes can systematically reach consumers with higher WTP. Similarly, for specification (5c) and (5d), we expect $\lambda^{NHC} < 0$ and $\lambda^{NCR} < 0$. We expect that, the larger the number of items sold per store, the more consumers will be exposed to the different products of the same manufacturer, which may, in turn, increase brand familiarity; as a result, we expect negative signs for $\lambda^{NHCItem}$ and $\lambda^{NCRItems}$, and, overall $\lambda^{NHC} + \lambda^{NHCItems} * \text{Items} < 0$ and $\lambda^{NCR} + \lambda^{NCRItems} * \text{Items} < 0$.

The variables in specification (5a)–(5d) capture the overall presence of different health claims and credence attributes in a manufacturer's portfolio. It is, however, possible that a manufacturer producing more products may be more likely to offer a larger number of health claims or overall credence attributes in their portfolios; if that was the case, the hypothesised effects illustrated above may be driven by an overall effect of product-line length and the additional beneficial image that manufacturers can experience from it;[9] in fact as Draganska and Jain (2005) indicate, longer product-line length can increase brand loyalty and allow charging higher prices. In order to isolate the effect of the presence of products with credence attributes on σ_u^2, separated from that of a manufacturer having a larger number of products, we parameterise the following four specifications of equation (3):

$$\sigma_u^2 = \exp(\lambda_0 + \lambda^{N-PROD}\text{N\_PROD} + \lambda^{N-PRODHC}\text{N\_PRODHC}); \tag{6a}$$

$$\sigma_u^2 = \exp(\lambda_0 + \lambda^{N-PROD}\text{N\_PROD} + \lambda^{N-PRODCR}\text{N\_PRODCR}); \tag{6b}$$

$$\sigma_u^2 = \exp(\lambda_0 + \lambda^{Sh-PRODHC}\text{Sh\_PRODHC}); \tag{6c}$$

$$\sigma_u^2 = \exp(\lambda_0 + \lambda^{Sh-PRODCR}\text{Sh\_PRODCR}); \tag{6d}$$

where N_PROD measures the total number of products in the manufacturer's offerings; N_PRODHC and N_PRODCR measure, respectively, the number of products with health claims and credence attributes that a manufacturer offers; Sh_PRODHC and Sh_PRODCR are the ratios N_PRODHC/N_PROD and N_PRODCR/N_PROD, respectively.

9 We thank an anonymous reviewer for raising this point.

In order for our hypotheses to be confirmed, we expect $\lambda^{\text{N-PRODHC}} < 0$ and $\lambda^{\text{N-PRODCR}} < 0$ and, additionally, we expect σ_u^2 to decline more with the number of products with health claims or with credence attributes than with the overall number of product offerings, or $\lambda^{\text{N-PRODHC}} < \lambda^{\text{N-PROD}}$ and $\lambda^{\text{N-PRODCR}} < \lambda^{\text{N-PROD}}$. Similarly, we expect $\lambda^{\text{Sh-PRODHC}} < 0$ and $\lambda^{\text{Sh-PRODCR}} < 0$. If these conditions are met, then it is the presence of credence attributes that allows manufacturers to price their products closer to the buyers' price frontier, and not the overall length of product line, as expressed by the total number of products in the market.

3.2. Data and variables

The data used in the estimation come from SymphonyIRI Group and contain monthly sales information (point-of-sale) of yoghurts from the entire Italian market (17 IRI regions[10]) encompassing a 25-month period between 29 November 2010 and 31 December 2012. The data contain information on volume sold and value of sales, price (EUR/l), percentage of stores selling each product and number of items sold in the stores. The IRI data separate yoghurts with health claims from others and also provide detailed information on vendors, brands, flavours, fat content, drinkability, whether a yoghurt is organic or labelled as 'natural', whether it is targeted at children, and a series of information related to packaging and product distribution. The information contained in the database was cross-validated using information retrieved from manufacturers' websites, the front-of-package and nutritional labels.

The vector of credence attributes $\mathbf{x}^{\text{CA}}$ contains six indicator variables, one for each health claim, one for 'organic' and one for 'natural.' Circa 30 per cent of products in our sample have health claims, which are classified in four classes: 'enhancing the immune system' (*Immunity*, 11.4 per cent of the sample), 'sustaining bowel regularity' (*Regularity*, 14.4 per cent), 'lowering or managing cholesterol level' (*Chol. Reduction*, 3.4 per cent) and 'supporting bone health' (*Bone Health*, 1.1 per cent). Approximately 9 per cent of the products in our sample are sold as 'organic' (*Organic*, 7.4 per cent) or 'natural' (*Natural*, 1.5 per cent).

The vector of non-credence attributes $\mathbf{x}^{\mathbf{NOC}}$ includes seven indicator variables capturing the products' flavours (*Plain* and *Fruit Flavours*), fat content (*Low Fat* and *Fat Free*), and whether the product is drinkable (*Drinkable*), contains added fibre (*Fibre*) and is lactose free (*Lactose Free*). The vector of packaging variables $\mathbf{x}^{\boldsymbol{P}}$ includes four indicator variables that capture whether the product was sold in a glass jar (*Glass Pack*), whether it has an additional compartment with cereals and/or chocolate (*Two Compartments*) and whether it is sold in packages between 300 and 500 ml (*Medium Pack*) or larger than 500 ml (*Large Pack*). The vector of retail-specific variables $\mathbf{x}^{\boldsymbol{R}}$ contains three variables: the average number of product items sold in stores (*Items*), the percentage of products sold under promotion (*% Sales Prom*) and the percentage

10 Although the Italian regions are 20, SymphonyIRI groups data from Piedmont and Aosta Valley, Abruzzo and Molise, Basilicata and Calabria, resulting in 17 'IRI regions'.

of outlets offering a product conditional on it being available in a given store, i.e. the average weighted distribution (AWD).[11]

After eliminating products with local distribution and products whose attribute profile could not be verified, the final database consisted of 54,386 observations including 220 products with unique combinations of attributes, encompassing 59 brands sold by 13 leading manufacturers.[12] Summary statistics of variables included in the model are reported in Table 1.

Below we present some descriptive test statistics to assess whether the distribution of prices in our data differs conditional on the presence of credence attributes (the four health claims discussed above, organic and natural). The average price of yoghurts without credence attributes is 3.897 EUR/l with a standard deviation of 1.282, whereas that of products with credence attributes is 4.855 EUR/l with a standard deviation of 1.275 and the coefficients of variation are 0.329 and 0.262, respectively. These values indicate that the price distribution of yoghurts without credence attributes is 25.3 per cent more dispersed than that of products with credence attributes. This finding is supported by the results of Kolmogorov–Smirnov tests for equality in distribution: the null hypothesis is that the price distributions of yoghurts with and without credence attributes are statistically equal can be rejected at the 1 per cent probability level.[13] The difference in distribution can also be visualised in the box plots and kernel density plots presented in Figure 2. The evidence that prices are less dispersed for products with credence attributes than for those without lends preliminary support to our hypothesis that the presence of credence attributes may allow manufacturers to consistently set prices at higher levels closer to the buyer's price frontier.

3.3. Estimation

Following the notation in Kumbhakar and Lovell (2000), our hedonic price model can be rewritten as $P^{\tau}_{jmt} = f(\mathbf{x}, \boldsymbol{\beta}) + \varepsilon_{jmt} = f(\mathbf{x}, \boldsymbol{\beta}) + v_{jmt} - u_{jmt}$,

11 Even though none of the retail variables are, strictly speaking, 'product attributes', their inclusion is necessary because products' store presence can be used strategically by retailers and can affect pricing strategies; thus, their omission could lead to omitted variable bias.

12 The original scanner dataset used in this analysis is the same as that used by Bimbo, Bonanno and Viscecchia (2016). Similar to their work, only cow milk yoghurt products for adults are retained in the data; additionally, we discarded private labels, whose attributes could not be verified, and those products whose functional attributes were classified in the 'other functionality' aggregate by IRI. However, for our analysis we excluded products produced by eight small/local producers, which appeared in the data only in limited geographical areas and for limited time periods. Maintaining these products in the data caused unstable SF estimates and convergence issues. As the objective of the current analysis is that of studying the nature of the systematic departure from the hedonic price curve, and not necessarily to provide a precise characterisation of the equilibrium marginal prices of different attributes (which was the goal of Bimbo, Bonanno and Viscecchia (2016)), we preferred to operate with a less noisy dataset by eliminating those products. Even though we ultimately eliminated 107 of the 327 products included in the dataset used by Bimbo, Bonanno and Viscecchia (2016), the number of usable observations was only 9.4 per cent lower than that used by those authors.

13 The value of the combined D-statistics for the Kolmogorov–Smirnov test is 0.0356 for a p-value of 0.000.

Table 1. Descriptive statistics (N = 54,386)

Variable	Mean	SD	Min	Max
Price	4.255	1.361	0.890	15
Credence attributes				
Chol. Reduction	0.034	0.181	0	1
Immunity	0.114	0.318	0	1
Regularity	0.144	0.351	0	1
Bone Health	0.011	0.107	0	1
Natural	0.015	0.120	0	1
Organic	0.074	0.261	0	1
Non-credence attributes				
Plain	0.294	0.455	0	1
Fruit Flavours	0.502	0.500	0	1
Other Flavours (excluded)	0.205	0.404	0	1
Regular (Excluded)	0.482	0.500	0	1
Low Fat	0.261	0.439	0	1
Fat Free	0.257	0.437	0	1
Lactose Free	0.020	0.139	0	1
Drinkable	0.216	0.412	0	1
Fibre	0.060	0.238	0	1
Packaging characteristics				
Glass Pack	0.022	0.146	0	1
Two Compartments	0.096	0.294	0	1
Regular Pack (excluded)	0.751	0.432	0	1
Medium Pack	0.249	0.433	0	1
Large Pack	0.001	0.036	0	1
Retail characteristics				
Num. Items	2.990	3.011	0	29
% Sales Prom	0.147	1.438	0	100
AWD	31.331	28.502	0	100

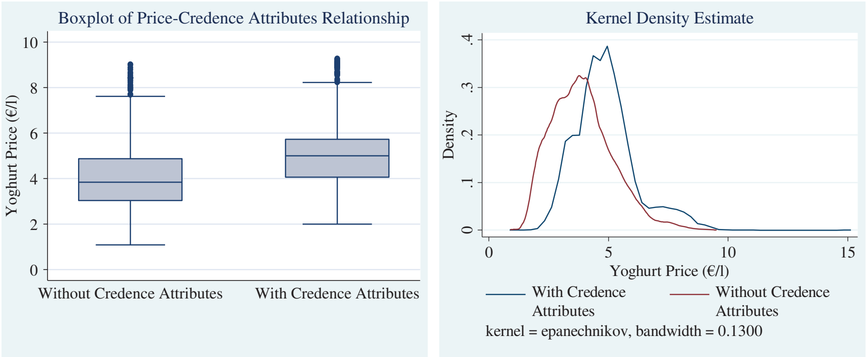

Fig. 2. Dispersion of yoghurt prices conditional on the presence of credence attributes. Left panel: box plots of yoghurt prices; right panel: kernel density estimates of yoghurt prices.

where $v \sim N(0, \sigma_v^2)$ and $u \sim N^{+}(0, \sigma_u^2)$ and its parameters are to be estimated by maximising the likelihood function,

$$L = \prod_j \prod_m \prod_t \frac{2}{\sigma} \phi\left(\frac{\varepsilon_{jmt}}{\sigma}\right) \Phi\left(\delta \frac{\varepsilon_{jmt}}{\sigma}\right); \tag{7}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$; $\delta = \frac{\sigma_u}{\sigma_v}$, $\phi(\bullet)$ and $\Phi(\bullet)$ are the standard normal *pdf* and *CDF*, respectively.

Wald tests can be performed on the estimated standard deviation of the half-normal[14] error σ_u to indicate whether the data support the use of SF regression: in the context of our analysis, failing to reject the null of $\sigma_u = 0$, indicates no systematic departure from the estimated buyer's price frontier; also, given our specifications of σ_u, failing to reject the null, $\sigma_u = 0$, indicates that the presence of products carrying credence attributes does not affect a supplier's ability to achieve higher prices. Alternative specifications of σ_u^2 consistent with equation (5a)–(5d) and equation (6a)–(6d) are estimated to test whether the presence of more products containing credence attributes results in prices closer to the buyers' price frontier. Data manipulation and estimation were performed using STATA version 13.

4. Empirical results

Table 2 presents the estimated parameters obtained from the different specifications of the hedonic model estimated using SF including a half-normal one-sided error with homoscedastic variance, which is referred to below as the 'baseline SF specification', as well as the heteroscedastic specifications of σ_u^2 consistent with equations (5a)–(5d) and (6a)–(6d).

The Box–Cox exponent parameter τ was estimated to be 0.2026. The Box–Cox specification using this exponent was determined to be preferred to linear, log-linear and multiplicative inverse specifications by means of likelihood ratio tests. The estimated coefficients associated with 'retail-specific variables' as well as brand-level fixed-effects and monthly and regional indicator variables are omitted for brevity but available upon request.

14 Whereas this paper assumes that the inefficiency term u follows a half-normal distribution, it should be noted that several other alternative distributions have been suggested in the literature, such as the truncated normal distribution, the exponential distribution, the gamma distribution and, more recently, the truncated Laplace (see Parmeter and Kumbhakar, 2014). Studies in the SFA literature usually do not compare estimates and differences in inference across different distributional assumptions. Greene (1990) tested for differences across the four main distributional specifications used for u in the literature, i.e. half-normal, truncated normal, exponential and gamma. He found almost no difference in average inefficiency levels for his sample of electric utility providers. Furthermore, Kumbhakar and Lovell (2000) calculated the rank correlations among the inefficiency estimates from these four models and found rank correlations in the range of 0.75–0.98. Models requiring no distributional assumptions on the inefficiency term are a recent development of the SFA literature. This approach has been followed by Horrace and Parmeter (2011), Tran and Tsionas (2009) and Parmeter, Wang and Kumbhakar (2017).

Table 2. SF results

	OLS	SF baseline	Equation (5a)	Equation (5b)	Equation (5c)	Equation (5d)	Equation (6a)	Equation (6b)	Equation (6c)	Equation (6d)
Credence attributes										
Chol. Red	0.151***	0.145***	0.152***	0.156***	0.150***	0.148***	0.143***	0.140***	0.146***	0.142***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Immunity	0.023***	0.023***	0.025***	0.028***	0.025***	0.024***	0.021***	0.020***	0.022***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Regularity	0.022***	0.018***	0.024***	0.03***	0.023***	0.021***	0.016***	0.013***	0.019***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Bone Health	0.257***	0.211***	0.193***	0.203***	0.195***	0.197***	0.195***	0.200***	0.197***	0.203***
	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Natural	0.172***	0.126***	0.12***	0.104***	0.119***	0.115***	0.125***	0.126***	0.121***	0.118***
	(0.010)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Organic	0.130***	0.088***	0.091***	0.089***	0.09***	0.086***	0.090***	0.091***	0.092***	0.092***
	(0.010)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Non-credence attributes										
Plain	−0.013***	−0.013***	−0.01***	−0.01***	−0.01***	−0.011***	−0.010***	−0.011***	−0.010***	−0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Fruits	−0.008***	−0.005***	−0.003***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***	−0.003***	−0.005***
	(0.001)	(0.001)	0.000	0.000	0.000	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Low Fat	−0.018***	−0.022***	−0.021***	−0.02***	−0.021***	−0.022***	−0.021***	−0.021***	−0.021***	−0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fat Free	−0.011***	−0.014***	−0.011***	−0.009***	−0.012***	−0.012***	−0.012***	−0.012***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lactose Free	0.018***	0.003	0.002	0.004	0.000	−0.001	0.002	−0.002	−0.006*	−0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Drinkable	0.046***	0.043***	0.042***	0.039***	0.042***	0.042***	0.045***	0.045***	0.043***	0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fibre	−0.02***	−0.02***	−0.017***	−0.018***	−0.018***	−0.019***	−0.017***	−0.017***	−0.017***	−0.018***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Packaging attributes										
Glass Pack	0.194***	0.152***	0.142***	0.143***	0.144***	0.147***	0.147***	0.154***	0.142***	0.153***
	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
TwoComp.	0.001***	0.098***	0.096***	0.098***	0.096***	0.096***	0.095***	0.095***	0.096***	0.097***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Medium Pack	−0.033***	−0.038***	−0.041***	−0.039***	−0.039***	−0.04***	−0.041***	−0.043***	−0.043***	−0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Large Pack	−0.071***	−0.084***	−0.085***	−0.086***	−0.084***	−0.085***	−0.083***	−0.085***	−0.089***	−0.088***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.194***	0.152***	0.142***	0.143***	0.144***	0.147***	1.300***	1.300***	1.302***	1.301***
	(0.010)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Ln (σ_v^2)		−7.171***	−7.28***	−7.213***	−7.304***	−7.288***	−7.237***	−7.244***	−7.325***	−7.187***
		(0.019)	(0.020)	(0.018)	(0.019)	(0.020)	(0.025)	(0.021)	(0.020)	(0.020)
σ_v		0.028***	0.026**	0.027**	0.026**	0.026**	0.027***	0.027***	0.026***	0.028***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(σ_u^2)		−6.024***								
		(0.020)								
σ_u		0.049***								
		(0.000)								
σ_u/σ_v		1.774***								
		(0.001)								
One Health Claim			−0.500***							
			(0.029)							
Two Health Claims			−0.676***							
			(0.032)							
Three Health Claims			−1.624***							
			(0.086)							
Four Health Claims			−1.619***							
			(0.062)							
N HealthClaims					−0.303***					
					(0.013)					
N Health Claims * Items per Store					−0.028***					
					(0.003)					

(*continued*)

Table 2. (*continued*)

	OLS	SF baseline	Equation (5a)	Equation (5b)	Equation (5c)	Equation (5d)	Equation (6a)	Equation (6b)	Equation (6c)	Equation (6d)
One Credence				−1.592***						
				(0.039)						
Two Credence				−1.026***						
				(0.038)						
Three Credence				−2.564***						
				(0.117)						
Four Credence				−2.411***						
				(0.076)						
N Credence						−0.245***				
						(0.012)				
N Credence * Items per Store						−0.032***				
						(0.003)				
N Products							0.002	0.001		
							(0.002)	(0.002)		
N Products with Health Claims							−0.097***			
							(0.005)			
N Products with Credence Attributes								−0.082***		
								(0.004)		
N Products with Health Claims / N Products									−1.673***	
									(0.049)	
N Products with Credence Attributes / N Products										−1.188***
										(0.050)
Constant			−5.395***	−4.652***	−5.405***	−5.437***	−5.661***	−5.623***	−5.475***	−5.612***
			(0.021)	(0.030)	(0.019)	(0.020)	(0.027)	(0.027)	(0.018)	(0.021)

Note. *, ** and *** are 10, 5 and 1 per cent critical levels. Standard errors in parentheses. Retailer variables, monthly dummies and brand-level and region-level fixed-effects coefficients are omitted for brevity.

The estimated coefficients are relatively robust for different specifications of the variance of the half-normal error u, as one can note by comparing estimates reported in the top panel of Table 2. Also, across all specifications of σ_u^2, we reject the null hypothesis of $\sigma_u^2 = 0$, supporting the existence of a systematic departure from the buyer's price frontier. In particular, the estimated ratio σ_u/σ_v from the baseline SF specification shows that the standard deviation of the half-normal component of the error term is about 1.8 times as large as that of the idiosyncratic residual, indicating that price inefficiencies lead to twice as much price variation compared to the dispersion of prices above and below the estimated hedonic curve.

Focusing on the estimated credence attributes parameters of the hedonic price function, we find four of them to have the largest effect on price: claims supporting bone health (*Bone Health*), whose coefficients range from 0.193 to 0.211 (specification (5a) and baseline specification, respectively); lowering blood cholesterol level (*Chol. Reduction*), with coefficients of 0.140 (specification (6b)) and 0.156 (specification (5b)); *Natural*, with coefficients between 0.104 (specification (5b)) and 0.126 (baseline specification and (6b)) and *Organic*, with coefficients between 0.086 (specification (5d)) and 0.092 (specification (6c) and (6d)). The coefficients for *Immunity* and *Regularity*, although statistically significant, are considerably smaller than those of the other four credence attributes. Most non-credence attributes do not contribute positively to prices, with the exception of *Drinkable*, whose coefficient varies between 0.039 (specification (5b)) and 0.045 (specification (6a)), and *Glass Pack* and *Two Compartments*, which result in coefficients ranging from 0.142 (specification (5a)) and 0.154 specification (6b) and from 0.196 to 0.198. Last, as one may expect, the higher the packaging size, the higher the price discount. Thus, overall, these results point to credence attributes, drinkable texture, glass packaging and the presence of a second ingredient compartment as sources of effective product differentiation.

The results presented in the bottom section of Table 2 show the estimated $\log(\sigma_u^2)$ and its components for the baseline SF model specification, as well as its constant terms for the specifications (5a)–(5d) and (6a)–(6d) to be statistically different from zero, which indicates that the data support the existence of systematic departures from the buyers' price frontier. Also, as hypothesised, all coefficients for the shifters of σ_u^2 in equations (5a)–(5d) are negative. The magnitude of the coefficients for specification (5a) and (5b) grows larger with the number of credence (or functional) attributes carried in a manufacturer's portfolio; however, the coefficients associated with the *Three Health Claims* and *Four Heath Claims* in specification (5a) and those of *Three Credence* and *Four Credence* in specification (5b) are not statistically different than one another. Furthermore, in specification (5b), the *One Credence* coefficient is larger in magnitude than that of *Two Credence*. In specification (5c) and (5d), the estimated coefficients associated with the actual number of functional/health claims, credence attributes and those of their interactions with the number of product items sold in the store are both negative and statistically significant.[15]

The coefficients for the shifters of σ_u^2 in equation (6a)–(6d) corroborate the findings of the other four specifications, supporting that the presence of a larger number of products carrying health claims/credence attributes is associated with smaller departures from the buyer's price frontier. The results of specification (6a) and (6b) also show that, whereas the total number of products in a manufacturer's portfolio do not affect σ_u^2 in a statistically significant way, both the number of products carrying health claims and that of products with credence attributes result in negative and statistically significant coefficients, suggesting that a larger number of products on the market does not necessarily support manufacturer efforts to reach consumers with higher WTP, but that having more products with credence attributes can achieve that goal. The results of specification (6c) and (6d), support this finding by showing that, as the fraction of products with health claims and credence attributes increases, manufacturers will be more likely to price their products closer to the buyer's price frontier.

The estimated average implicit prices associated with different product attributes and for ordinary least squares (OLS), baseline SF specification and across specification (5a)–(5d) are calculated following Waldrop, McCluskey and Mittelhammer (2017) and are presented in Table 3. The implicit prices obtained for specification (6a)–(6d) are similar to those reported in the text and are omitted for brevity. An interesting result is that, in most cases, the implicit prices calculated from the SF estimates are smaller than the OLS ones, or in the case of those resulting in a discount (such as some of the non-credence attributes), they show higher magnitudes (that is, indicating a larger discount).

All credence attributes positively affect yoghurt prices, with claims of supporting bone health (*Bone Health*) and lowering cholesterol level in the blood (*Chol. Reduction*) outperforming all other health claims as well as *Natural* and *Organic*. Specifically, the health claims with the lowest implicit prices are 'Regulating the intestinal tract' (*Regularity*), with estimated implicit prices ranging from 0.298 EUR/l (baseline specification) to 0.5100 EUR/l (specification (5b)), and 'Supporting the immune system' (*Immunity*), with implicit price varying from 0.385 (baseline) to 0.473 EUR/l (5b). These modest implicit prices may be due to the limited level of differentiation supported by these attributes, as products carrying them have been on the market for several years (Bimbo, Bonanno and Viscecchia, 2016). The implicit price of *Cholesterol Reduction* claims varies from 2.461 to 2.642 EUR/l, whereas

15 Additionally, the estimated coefficients reported in the bottom panel of Table 2 were used to estimate the variance of the half-normal error as in equation (5a)–(5d) in the function of the number of health claims and credence attributes. Although the magnitudes of the estimated σ_u^2 in the absence of credence attributes/health claims differ slightly across specifications and show that the variance of the systematic departure from the buyer's price frontier is between 4.9 and 10 times smaller for those manufacturers that include four credence attributes in their portfolios than for those that have none, our results support the notion that adding credence attributes to its portfolio can allow a manufacturer to exert higher prices. These results are omitted for brevity and available upon request.

Table 3. Implicit prices – model specification (5a)–(5d).

Variables	OLS	SF Baseline	Spec. (5a)	Spec. (5b)	Spec. (5c)	Spec. (5d)
Credence attributes						
Chol. Reduction	2.2893***	2.4605***	2.5808***	2.6421***	2.5614***	2.5282***
	(0.0295)	(0.0332)	(0.0293)	(0.0296)	(0.0301)	(0.0307)
Immunity	0.3437***	0.3853***	0.4289***	0.4730***	0.4253***	0.4109***
	(0.0176)	(0.0197)	(0.0188)	(0.0194)	(0.0187)	(0.0190)
Regularity	0.3408***	0.2984***	0.4074***	0.5100***	0.3942***	0.3541***
	(0.0237)	(0.0266)	(0.0256)	(0.0276)	(0.0249)	(0.0251)
Bone Health	3.8919***	3.5832***	3.2851***	3.4325***	3.3183***	3.3564***
	(0.1517)	(0.0463)	(0.0471)	(0.0428)	(0.0462)	(0.0464)
Natural	2.6122***	2.1331***	2.0389***	1.7586***	2.0267***	1.9567***
	(0.1498)	(0.0409)	(0.0440)	(0.0367)	(0.0432)	(0.0427)
Organic	1.9721***	1.4957***	1.5503***	1.5103***	1.5389***	1.4603***
	(0.1502)	(0.0426)	(0.0479)	(0.0403)	(0.0476)	(0.0460)
Non-credence attributes						
Plain	−0.1973***	−0.2169***	−0.1680***	−0.1627***	−0.1714***	−0.1842***
	(0.0088)	(0.0095)	(0.0091)	(0.0089)	(0.0092)	(0.0093)
Fruit Flavours	−0.1216***	−0.0869***	−0.0574***	−0.0674***	−0.0612***	−0.0687***
	(0.0080)	(0.0087)	(0.0085)	(0.0082)	(0.0085)	(0.0086)
Low Fat	−0.2789***	0.3767***	−0.3651***	−0.3402***	−0.3658***	−0.3711***
	(0.0204)	(0.0222)	(0.0196)	(0.0201)	(0.0193)	(0.0197)
Fat Free	−0.1708***	−0.2427***	−0.1908***	−0.1597***	−0.1979***	−0.2021***
	(0.0094)	(0.0105)	(0.0107)	(0.0109)	(0.0106)	(0.0106)
Lactose Free	0.2691***	0.0425	−0.0284	−0.0664	0.0038	−0.0137
	(0.0464)	(0.0506)	(0.0491)	(0.0535)	(0.0485)	(0.0494)

(*continued*)

Table 3. (*continued*)

Variables	OLS	SF Baseline	Spec. (5a)	Spec. (5b)	Spec. (5c)	Spec. (5d)
Drinkable	0.6943***	0.7265***	0.7069***	0.6603***	0.7107***	0.7159***
	(0.0191)	(0.0209)	(0.0185)	(0.0191)	(0.0182)	(0.0186)
Fibre	−0.2989***	−0.3405***	−0.2878***	−0.2962***	−0.2986***	−0.3159***
	(0.0233)	(0.0258)	(0.0227)	(0.0233)	(0.0224)	(0.0227)
Packaging attributes						
Glass Pack	2.9460***	2.5841***	2.4109***	2.4168***	2.4614***	2.5110***
	(0.1500)	(0.0469)	(0.0497)	(0.0461)	(0.0490)	(0.0491)
Two Compartments	1.5077***	1.6694***	1.6351***	1.6557***	1.6284***	1.6377***
	(0.0225)	(0.0248)	(0.0231)	(0.0224)	(0.0232)	(0.0235)
Medium Pack	−0.4956***	−0.6405***	−0.7023***	−0.6571***	−0.6694***	−0.6772***
	(0.0115)	(0.0129)	(0.0125)	(0.0129)	(0.0129)	(0.0130)
Large Pack	−1.0753***	−1.4180***	−1.4531***	−1.4526***	−1.4319***	−1.4461***
	(0.1097)	(0.1178)	(0.1137)	(0.1253)	(0.1115)	(0.1134)

Note: *, ** and *** are 10, 5 and 1 per cent critical levels. Standard errors in parentheses. Implicit prices are obtained following Waldrop, McCluskey and Mittelhammer (2017).

that of *Bone Health* exceeds 3 EUR/l across models (from 3.285 EUR/l for specification (5a) to 3.892 EUR/l for OLS). The high market valuations of *Cholesterol Reduction* and *Bone Health* are in line with the findings of previous studies (Ares and Gámbaro, 2007; Siegrist, Stampfli and Kastenholz, 2008; Bimbo, Bonanno and Viscecchia, 2016). *Organic* and *Natural*, which are not associated with specific benefits for consumers, show average implicit prices ranging from 1.460 EUR/l (specification (5d)) to 1.972 EUR/l (OLS) and from 1.759 EUR/l (5b) to 2.612 EUR/l (OLS), respectively, according to SF estimates. Overall, these implicit prices are likely due to a combination of higher production cost (at least, in the case of 'organic') and the fact that consumers are willing to pay a premium price for features having a 'halo effect' (Schuldt and Schwarz, 2010; Schuldt, 2013), as products labelled 'organic' and 'natural' that are often perceived as healthier than regular ones (e.g. Lodorfos and Dennis, 2008; Schuldt and Schwarz, 2010).

The estimated implicit prices for the non-credence attributes are reported in the second part of Table 4. *Plain* and *Fruit flavours* show negative implicit

Table 4. Robustness checks: estimated half-normal error variance (σ_u^2 ; specification (5d)), and implicit prices for credence attributes. Alternative functional forms

	Box–Cox (λ = 0.2026)	Log-linear	Square root	Linear
Estimated half-normal error variance (σ^2_u)				
No Credence	0.0044***	0.0657***	0.0520***	0.5276***
	(0.0001)	(0.0012)	(0.0012)	(0.0218)
One Credence	0.0030***	0.0467***	0.0349***	0.2752***
	(0.0001)	(0.0007)	(0.0009)	(0.0177)
Two Credence	0.0022***	0.0339***	0.0243***	0.1526***
	(0.0000)	(0.0006)	(0.0008)	(0.0155)
Three Credence	0.0017***	0.0264***	0.0187***	0.1031***
	(0.0000)	(0.0006)	(0.0008)	(0.0140)
Four Credence	0.0009***	0.0152***	0.0092***	0.0302***
	(0.0000)	(0.0005)	(0.0007)	(0.0062)
Implicit prices				
Chol. Reduction	2.5282***	3.1439***	2.3769***	2.1182***
	(0.0307)	(0.0493)	(0.0299)	(0.0295)
Immunity	0.4109***	0.4346***	0.3253***	0.1806***
	(0.0190)	(0.0193)	(0.0184)	(0.0181)
Regularity	0.3541***	0.3679***	0.2826***	0.1667***
	(0.0251)	(0.0251)	(0.0247)	(0.0243)
Bone Health	3.3564***	4.6234***	3.1561***	2.8133***
	(0.0464)	(0.0883)	(0.0461)	(0.0481)
Natural	1.9567***	2.3852***	1.7186***	1.3258***
	(0.0427)	(0.0608)	(0.0423)	(0.0433)
Organic	1.4603***	1.6685***	1.2827***	1.0004***
	(0.0460)	(0.0589)	(0.0450)	(0.0446)

Note. *, ** and *** are 10, 5 and 1 per cent critical levels. Standard errors in parentheses. The implicit prices for the Box–Cox and square root transformation are obtained following Waldrop, McCluskey and Mittelhammer (2017). The implicit prices for the log-linear model are calculated using Kennedy (1981) adjustments times the average price.

prices and for most estimates the OLS ones are higher than those obtained with SF, indicating that for products carrying these flavours, price discounts will be more marked further away from the buyer's price frontier (i.e. at lower price levels). These results support other findings that 'flavour' may not be an effective price differentiation tool in the Italian yoghurt market (e.g. Bonanno, 2013). The estimated implicit prices for *Low Fat* and *Fat Free* are also negative; however, the implicit prices obtained from SF coefficients are larger than the OLS ones, indicating that attributes related to reduced-fat content generate a higher discount at the buyer's price frontier than at lower price levels, consistent with other research indicating that fat content does not seem to be a source of product differentiation in the Italian yoghurt market (Carlucci *et al.*, 2013; Bonanno, 2013).

The estimated implicit price of *Drinkable* obtained from the SF coefficients varies between 0.660 and 0.763 EUR/l, in line with the previous findings that Italian yoghurt consumers prefer drinkable yoghurts to regular ones (Bonanno, 2013); also, as the SF estimated implicit prices are higher than the OLS ones on average, this suggests that this attribute may be more important for consumers with the highest WTP. An interesting result is that for *Lactose Free*, the OLS implicit price is positive (0.269 EUR/l), whereas the SF ones are all not statistically different than zero, suggesting that while this feature may help achieve higher prices for products targeting consumers with lower WTP, its contribution to product differentiation is limited at higher prices. This could be the result of consumers with higher WTP substituting lactose-free dairy products with specific medicines that allow them to consume regular dairy products. The presence of added fibre (*Fibre*) affects yoghurt's price negatively, with implicit prices varying from −0.288 to −0.340 EUR/l, suggesting that adding fibre to a yoghurt may result in a price reduction regardless of its price level. This finding is supported by other studies highlighting that consumers can be sceptical of features 'unnaturally' or artificially added to a product (Krutulyte *et al.*, 2011; Annunziata and Vecchio, 2013).

The estimated implicit prices for the packaging characteristics are shown in the bottom section of Table 4. Glass packaging (*Glass Pack*) and the presence of a two-compartment package (*Two Compartments*) show positive implicit prices. Even though the existence of a price premium associated with glass packaging may reflect the higher cost of the material (Silayoi and Speece, 2004), the large implicit prices indicate that using glass packaging may also confer an image of higher quality. The estimated coefficients associated with variables capturing different package size (*Medium Pack* and *Large Pack*) are negative, consistent with the expectation that unitary price declines with size; the SF implicit price discounts for both *Medium Pack* and *Large Pack* are larger than the OLS ones, indicating larger discounts at the buyer's price frontier, particularly for the latter size.

5. Robustness checks

The estimates presented above are obtained using a Box–Cox functional form, as illustrated in equation (4). As Cropper, Deck and McConnell (1988) argue that simple functional forms (e.g. linear, log-linear, Box–Cox transformations) outperform more flexible functional forms in the presence of omitted variables bias,[16] we compare the results obtained using the Box–Cox transformation with those of linear, square root and log-linear functional forms by means of the estimated variance of the half-normal error and the estimated marginal prices of the credence attributes.

The estimates presented in the top panel of Table 4 show that our results are qualitatively robust in terms of the patterns observed in the variance of the half-normal error, capturing the systematic dispersion from the price frontier as function of the number of credence attributes in a manufacturer's portfolio. In the first place, it should be noted that even though the estimated σ_u^2 vary considerably with the functional form used, their magnitudes are in line with the estimated σ_v^2 for each different functional forms ($\sigma_v^2 = 0.0007$ for the Box–Cox transformation; 0.0082 for the log-linear; 0.0122 for the square root transformation and 0.3260 for the linear, omitted from Table 4). Comparing the estimated average σ_u^2 for products of manufacturers without any credence attributes to those with manufacturers with four, we find the variance of the systematic departure from the buyer's price frontier to be between 4.3 (log-linear) and 17.5 (linear) times smaller for manufacturers with the largest number of credence attributes in our sample. The Box–Cox, square root and logarithmic forms lead to comparable ratios, between 4.3 and 5.6. Thus, our main finding that adding credence attributes to a manufacturer's portfolio can allow them to price closer to a buyer's price frontier, appears robust to the choice of functional form.

Also, the estimated average implicit prices of the credence attributes (in the bottom panel of Table 4) decline from the log-linear (obtained using Kennedy's (1981)) adjustment times the average sample price to the linear functional form. As one would expect, given the Box–Cox parameter of 0.2026, the Box–Cox model's implicit prices are close to those obtained using a square root functional form and they are positioned in-between those of the log-linear and linear models. It should be noted that, even though the estimated marginal prices do differ across functional forms, health claims concerning bone health and lowering blood cholesterol level always result in the two highest marginal prices among credence attributes, followed by 'natural' and 'organic' claims. The marginal prices of *Immunity* and *Regularity*,

16 The alternative functional forms considered in this section are simple parametric specifications used widely in the literature. However, other approaches are available: for example Ekeland, Heckman and Nesheim (2004) illustrate nonparametric transformation and instrumental variables methods to be applied to a general parametric setting. Alternatively, given the large presence of a large number of binary regressors in our model, a nonparametric approach as that discussed by Ouyang, Li and Racine (2009) could be implemented to identify only the relevant regressors in our model. We thank an anonymous referee for suggesting these alternative approaches.

are, again, smaller than those of the other credence attributes and their relative importance becomes even smaller as one goes from nonlinear functional forms to linear ones.

6. Price-efficiency estimates

The results discussed above highlight how regardless of: (i) the parameterisation of the half-normal portion of the error term and (ii) the functional form chosen for the hedonic price function, we find robust evidence of manufacturers' ability to price closer to the buyer's price frontier when the number of health claims or credence attributes in their portfolio increases. However, the results discussed so far do not quantify how 'close' to the price frontier the presence of products with credence attributes allows a manufacturer to price their product.

Following Kumbhakar and Parmeter (2010), expressing the dependent variable in logarithms, observation-specific estimates of $E(e^{-u_{jmt}})$ can be interpreted as a measure of price efficiency, that is, the ratio of the price observed in the data P_{jmt}, and the maximum attainable price, given a products' characteristics, $P*(\mathbf{x}_{jmt})$ or:[17]

$$\frac{P_{jmt}}{P*(\mathbf{x}_{jmt})} = e^{-u_{jmt}} \Leftrightarrow \log P_{jmt} = \log(P*(\mathbf{x}_{jmt})) - u_{jmt}. \quad (8)$$

Thus, we estimated the log-linear hedonic price equations using the different parametrisation of the half-normal disturbance term (equations (5a)–(5d) and (6a)–(6d)) to obtain the estimated price efficiency terms to assess the differences in price efficiency levels across manufacturers carrying different numbers of health claims or credence attributes.

Visual summaries of the conditional averages of the estimated price efficiency terms across model specifications are reported in Figure 3 (detailed estimates are omitted for brevity and available upon request). The top panels of Figure 3 include the average estimated price efficiency obtained using model specifications (5a), (5c), (6a) and (6c), conditional on the number of functional attributes in a manufacturer's portfolio (left panel), and the estimated price efficiency obtained using model specifications (5b), (5d), (6b) and (6d) conditional on the number of credence attributes in a manufacturer's portfolio (right panel). The results show that across the different parametrisations of σ_u^2, manufacturers' price efficiency increases with the number of health claims or credence attributes in their portfolio. On average, the overall increase in price efficiency is slightly less than 10 per cent: the estimated average values of price efficiency fluctuate from a minimum of approximately 0.825 (no health claims, model specification (5a); no credence attributes, specification (5d)) to a maximum of about 0.918 (four health claims, model (5a); four credence attributes, model (5b)).

17 We thank an anonymous reviewer for a comment leading to this extension of our analysis.

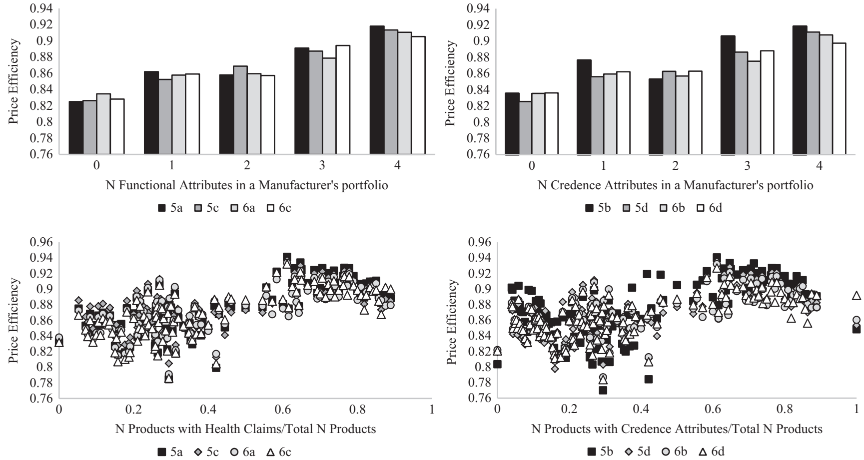

Fig. 3. Estimated average price efficiency in function of: number of functional attributes in a manufacturer's portfolio (top left panel); number of credence attributes in a manufacturer's portfolio (top right panel); ratio of the number of products with health claim over total number of products (bottom left panel); ratio of number of products with credence attributes over total number of products (bottom right panel). Log-linear hedonic price model specification; different parameterisation of the half-normal error term.

Even though our results suggest that carrying a larger number of health claims or credence attributes can result in improved price efficiency, they do not indicate whether manufacturers should aim to carry more products with these attributes in their product lines, regardless of their capacity (i.e. length of their product lines). This relationship is investigated by means of the values reported in the bottom panels of Figure 3, that is, scree plots of the average estimated price efficiency obtained under model specifications (5a), (5c), (6a) and (6c), conditional on the ratio of number of products with functional attributes over total number of products (left panel) and the average estimated price efficiency obtained using model specifications (5b), (5d), (6b) and (6d), conditional on the ratio of the number of products carrying a credence attribute over total number of products (right panel). Both graphs show an upward trend of the estimated average price efficiency, although reaching a maximum at a value of approximately 0.65, suggesting that Italian yoghurt manufacturers able to price their products closest to the buyer's price frontier have, on average, about two out of three products carrying either a health claim or a credence attribute.

7. Conclusions, limitations and future research

In this article, we assess whether manufacturers' investments in credence attributes enable them to reach systematically higher price levels. Using the Italian yoghurt market as a case study, based on a hedonic price model estimated by means of a SF estimator, we find evidence that manufacturers with larger portfolios of products carrying credence attributes can systematically reach consumers with a higher WTP. This suggests that introducing credence attributes to a producer's portfolio may lead to successful product differentiation and an increase in reputation, while other attributes seem to lead to lower price premiums once the buyer's price frontier is reached. As a result, firms that invest strategically in credence features may benefit from improved reputation and may be able to segment the market more effectively than other firms. Firms that lack the resources to include products carrying health claims in their portfolio may attempt to reach the buyer's price frontier by specialising in the niche of natural or organic products. In spite of the insights provided in this article, the value of our analysis should be contextualised, as our results can be expanded in different directions. First, our analysis focused on one specific case study, the Italian yoghurt market, which was chosen because of its richness in credence product attributes and because it lends itself well to the empirical approach used (hedonic price modelling). The ability of food manufacturers to product differentiate successfully by means of credence attributes should be confirmed by studying other product markets and geographical contexts. Second, our analysis does not explicitly take into account firms' costs related to providing credence attributes; even though our estimates point to the manufacturers' ability to reach higher prices, such higher prices may not result in higher profitability if the cost of providing credence attributes is prohibitively high. Thus, future research should formally assess the profitability of these attributes. Third, even though our results appear robust to both different parametric specifications of the half-normal error's variance, and to the functional form adopted, we did not verify whether our results are robust to different distributions for the inefficiency term. Different distributional assumptions of the inefficiency term, as well as non-parametric methods that do not require distributional assumptions (e.g. Parmeter, Wang and Kumbhakar (2017) and non-parametric estimation methods in general (e.g. Ouyang, Li and Racine, 2009), could be adopted in future research. Fourth, although we cannot exclude a priori the existence of market asymmetries on the consumers' and the manufacturers' sides, because our data do not contain detailed information on consumers' characteristics, we could only limit our analysis to studying the sources of price dispersion from the manufacturers' standpoint, using what could be seen as a 'production frontier' estimation approach. Future research using richer, more granular data containing both consumers' and manufacturers' characteristics could venture in investigating the existence of two sources of asymmetries, adapting the two-tiered, one-sided error estimator, *à la* Kumbhakar and Parmeter (2010), to the context of differentiated product markets.

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