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Price determination in the restaurant industry: the power of consumer opinion versus expert opinion

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ABSTRACT

Abstract

While efforts have been made to compare the effects of expert evaluation versus consumer-based evaluation on price determination within various sectors, there is no comparative evidence in relation to the restaurant industry. This paper fills that gap in the literature by applying hedonic price analysis to 338 Italian Michelin-starred restaurants and investigating, in particular, the role played in price determination by both gastronomic guides and consumer-based online platforms, which are tools largely used for culinary tourism. In contrast to user-based ratings, expressed by the scores available on the online travel platform TripAdvisor, expert evaluations for food, service and setting are proven to exert a strong and positive impact on prices. Results also show that creative cuisine is able to attract higher prices than other cuisine styles, confirming the prominent role of chefs' ingenuity in generating economic value.
Impact statement. This research contributes to restaurant management by showing the price determinants in fine-dining sector. The specific focus on comparing the role played in price determination by both gastronomic guides and consumer-based online platforms can inform restaurant operator and consumer choice within the field of gastronomic tourism. Although the analysis is limited to a specific scope (Italian Michelin-starred restaurants), it can offer a model to replicate in similar contexts.

Sebbene molti sforzi siano stati compiuti per confrontare gli effetti della valutazione di esperti rispetto alla valutazione basata sul consumatore sulla determinazione dei prezzi all'interno di vari settori, non ci sono prove comparative in relazione all'industria della ristorazione. Questo articolo colma la lacuna nella letteratura applicando l'analisi edonica dei prezzi a 338 ristoranti italiani, stellati Michelin, e indagando, in particolare, il ruolo svolto nella determinazione dei prezzi sia dalle guide gastronomiche che dalle piattaforme online basate sui consumatori, che sono strumenti ampiamente utilizzati per il turismo culinario. Contrariamente alle valutazioni basate sugli utenti, espresse dai punteggi disponibili sulla piattaforma di viaggi online TripAdvisor, le valutazioni degli esperti su cibo, servizio e ambiente hanno dimostrato di esercitare un forte e positivo impatto sui prezzi. I risultati mostrano inoltre che la cucina creativa è in grado di proporre prezzi più elevati rispetto ad altri stili di cucina, confermando il ruolo preminente dell'ingegno degli chef nella generazione di valore economico.
Dichiarazione di impatto. Questa ricerca contribuisce alla gestione della ristorazione mostrando le determinanti del prezzo nel settore della cucina raffinata. L'attenzione specifica al confronto del ruolo svolto nella determinazione dei prezzi sia dalle guide gastronomiche sia dalle piattaforme online basate sui consumatori può informare l'operatore della

ristorazione e guidare la scelta del consumatore nell'ambito del turismo gastronomico. Sebbene l'analisi sia limitata a un ambito specifico (ristoranti italiani stellati Michelin), assa può offrire un modello da replicare in contesti simili.

Keywords: hedonic price modelling, price determination, restaurant industry, expert evaluation, consumer-based evaluation

1 – Introduction

The "restaurant industry" is marked by a significant level of differentiation, as well as intense competition (Johnson *et al.*, 2005). Although restaurants fulfil well-identifiable needs, they deliver their products to the market in ways that can hardly be framed as homogeneous. This is reflected in the diverse range of prices for restaurant meals, which can vary from the low-cost options offered by fast food chains to the three-digit prices charged by high-end restaurants.

Economic theory posits that when products are highly differentiated and the market reflects competitive conditions, price difference is attributable to heterogeneous product quality (Snyder and Cotter, 1998). However, this assumes that consumers make their decisions relying on perfect information, which is not the case where restaurants are concerned. In fact, accurate evaluation and information gathering is made difficult as a result of restaurants being scattered geographically and because acquiring information can be problematic and expensive (Chossat and Gergaud, 2003). Moreover, evaluation is based on subjective criteria, and the nature of the product (food, service and setting) is experiential. The implication is that the actual quality of the product can only be truly assessed once consumed (Akerlof, 1970; Chossat and Gergaud, 2003).

Since the beginning of the twentieth century, the restaurant market has been inundated with an increasing proliferation of tools designed to reduce information gaps so that consumers can better identify and access the providers and products that best meet their preferences and budget constraints. Restaurant and gastronomic guides represent one type of tool that draws on the conceptual framework of expert selection, whereby expertise plays a key role in providing accurate information at a reasonable cost (Chossat and Gergaud, 2003; Gergaud *et al.*, 2007).

A comparable framework can be observed in related industries, one prominent example being the wine industry, wherein, besides providing consumers with product ratings and commentary, expert opinion drives purchasing decisions (Hilger *et al.*, 2011) and wine prices (Ozckowski, 1994; Cardebat *et al.*, 2014). More generally, expert opinion is frequently observed to be at play whenever information asymmetry subsists; this applies for both cultural industries (e.g. gastronomic, music and visual arts) and non-cultural industries (e.g. domestic appliances) (Wijnberg and Gemser, 1999).

Owing to the development of information and communication technologies, new modalities have emerged for coping with information asymmetries in the hospitality industry. In recent decades, the once-exclusive field of professional criticism witnessed its boundaries being progressively blurred due to disruptive transformations caused by various forms of digital media, including personal blogs, social networks and other user-generated content platforms such as websites (Kobez, 2019; Alaimo *et al.*, 2019).

Such tools benefit consumers by reducing risk, search time, buyer's remorse and group influence (Parikh *et al.*, 2014), thus providing consumers with useful alternatives to traditional means of obtaining information. In the case of restaurants, a prominent role is played by the consumer-based review platform, TripAdvisor, which is currently one of the most exhaustive databases for the tourism and hospitality sectors, among other options such as Yelp, Zomato and OpenTable.

Within this framework, this paper principally aims to provide evidence of the impact of gastronomic guides and online consumer-based review platforms on the determination of restaurant menu prices. Our study focuses on the high-end restaurant market in Italy, represented by establishments that can boast the most prestigious accolade in the sector: the Michelin stars, bestowed by the legendary Michelin Guide, which featured 372 establishments in its 2020 edition. More specifically, by employing hedonic price analysis (HPA) and drawing on the empirical literature on restaurant pricing to control for relevant attributes (Fogarty, 2012; Yim *et al.*, 2014), our study identifies the primary factors that affect price determination, as well as the role played by both expert and consumer opinion. In particular, the influence of both the Michelin Guide and Gambero Rosso guide is compared to that of TripAdvisor consumer ratings, so as to better understand their respective impacts on pricing of the two competing models (i.e. expert evaluation versus user-based evaluation).

This research study contributes to the literature in two ways.

First, in contrast to previous research, only the very upper segment of the dining industry is studied, our sample being restricted to establishments that held at least one Michelin star in 2020. The advantage of this choice is twofold. On the one hand, it creates a homogenous sample to focus on, thus containing potential empirical problems that may arise from the high heterogeneity that characterises the restaurant market. The impact of expert evaluation on pricing can, indeed, vary significantly across different market characteristics and segments, with the greatest effect expected on higher-end products, whose consumers are more inclined to invest time and effort in researching those products prior to purchase (Chen and McCluskey, 2018). As such, focusing exclusively on Michelin-starred restaurants also guarantees that the establishments chosen for inclusion in the data sample display greater stability, on average, in terms of reputation and performance. On the other hand, because only a modest number of establishments can boast such a prestigious accolade, data collection is more easily facilitated, and the field of application can be extended to encompass an entire country (in this case, Italy), which allows us to identify specific regional patterns, as well as capture a broader national picture, rather than mere territory-specific dynamics. This departs from previous research, which was limited to specific areas such as metropolises or single regions (Gergaud *et al.*, 2007; Gergaud *et al.*, 2010; Fogarty, 2012; Yim *et al.*, 2014).

Second, in addition to expert evaluations, consumer evaluations of cuisine, service and quality–price ratio (submitted as ratings via TripAdvisor) are accounted for in the hedonic pricing model. This allows us to measure the impact of the two types of evaluation and to compare their respective influence on restaurant meal prices. While previous efforts have been made to contrast the effects of expert versus consumer evaluations in various industries, such as wine (Oczkowski and Pawsey, 2019) and film (Peng *et al.*, 2013), to the best of our knowledge, this is the first comparative attempt applied to price determination in the restaurant market.

2 – Literature review

Price determination represents a fundamental strategic decision for companies in that it both affects revenue generation and functions as a signal to the market, enabling consumers to compare and select products that best meet their preferences and budget parameters (Papatheodorou and Apostolakis, 2012). In increasingly differentiated markets, consumers face complex purchase decisions as they seek to select products that contain unique bundles or 'packages' (Rosen, 1974) whose characteristics enable consumers to maximise utility (Costanigro and McCluskey, 2011). In a hedonic pricing framework, utility and value are not considered as inherent to a product but rather are determined by assessing the individual attributes of that product, as well as any external factors that may influence consumption and value, such as the particulars of consumers themselves and environmental factors. Market prices are determined by the sum of implicit prices for individual attributes – 'econometrically determined regressing the observed product price on its characteristics' (Gergaud *et al*., 2007) – according to the various attributes of the product (Costanigro and McCluskey, 2011). In this vein, HPA has been applied to various sectors, including food and beverage (Tronstad *et al*., 1992; McConnell and Strand, 2000; Huang and Lin, 2007; Ward *et al*., 2008), hospitality (Abrate *et al*., 2011; Rigall-I-Torrent and Fluvià, 2011; Schamel, 2012), wine (Oczkowski, 1994; Combris *et al*., 1997; Galati *et al*., 2017) and housing (Maurer *et al*., 2004).

Despite extensive application within the aforementioned market studies, HPA has garnered little interest in studies of the restaurant and food services industry (Yim *et al*., 2014; Bacon *et al*., 2016). Exceptions include Susskind and Chan (2000), Gergaud *et al*. (2007), Fogarty (2012), Yim *et al*. (2014) and Shin (2018). These studies, summarised in Table 1, investigated key determinants of restaurant pricing, namely critical reviews and ratings, as well as cuisine types and the physical attributes of the establishments, such as décor and amenities.

In line with the literature on price determination in wine markets (Jones and Storchmann, 2001; Ashton, 2016), empirical evidence shows that expert scores positively influence restaurant meal prices as well as company turnover and the reputation of chefs. A study by Gergaud *et al*. (2007) found that Parisian restaurants selected for inclusion in the Michelin Guide were able to charge 8 per cent more than non-selected restaurants, while the attribution of a Michelin star was associated with a 25 per cent price increase. Similarly, Shin (2018) found that Michelin-starred restaurants in New York City were able to charge higher prices as a consequence of their elevated status. Depending on the number of stars awarded, price could be increased by up to 80.2 per cent for three-starred establishments. This was confirmed by a qualitative analysis of restaurants in Europe that had been awarded at least two Michelin stars (Johnson *et al*., 2005), which revealed that the majority of the three-starred chef-proprietors who were interviewed for the study reported an increased turnover of at least 20 per cent after being awarded one or more Michelin star/s.

In a similar vein, a few studies have also analysed the effect on prices when restaurants are downgraded in the Michelin Guide. Snyder and Cotter (1998) found that in the two years following demotion, downgraded restaurants were able to increase prices up to 40 per cent lower than competitors who had retained the award. This finding is consistent with Gergaud *et al*. (2010), who demonstrated that in the top tier of the industry, as a consequence of acquired reputation, prices change even more when establishments are downgraded than when they are upgraded. While the aforementioned studies contribute to understanding which factors determine pricing in the restaurant market, as well as the role played by expert opinion, their findings are limited to distinct urban contexts (see Yim *et al*., 2014; Shin, 2018) and/or weakened by the high heterogeneity of samples in which vastly different restaurant segments are lumped together (see Fogarty, 2012).

Moreover, these studies do not account for recent trends in the nature of restaurant evaluation. For example, word of mouth is a major marketing tool for restaurants, although its impact is restricted by limited accessibility (Fields, 2014).

Table 1 – Overview of hedonic pricing model applications in restaurant market studies

AUTHOR	LOCATION	DEPENDENT VARIABLE AND MODEL	REGRESSORS
SUSSKIND AND CHAN (2000)	Toronto, Canada	Check average (Linear)	• Ratings of food quality, décor and service (Zagat) • Amenities (e.g. dress code, parking, takeaway service, smoking section, outdoor dining)
GERGAUD, GUZMAN AND VERARDI (2007)	Paris, France	Meal price (Log linear)	• Inclusion in the Michelin Guide • Michelin star/s awarded • Haute cuisine served • Ratings for food quality of food, décor and service (Zagat)
FOGARTY (2012)	Australia	Meal price (Log linear)	• Expert opinion • Wine list comment • BYO wine option • Location • Cuisine type • Restaurant capacity • Private dining room • Outdoor dining option
YIM, LEE AND KIM (2014)	Seoul, Korea	Meal price (Log linear)	• Ratings of food quality, décor and service (Zagat) • Blogger reviews • Parking • Cuisine type • Private dining room • Franchising • First-floor location
BACON, BESHARAT AND PARSA (2016)	New York, USA	Meal price (Linear)	• Ratings of food, décor and service (Zagat) • Cuisine type
SHIN (2018)	New York, USA	Meal price (Log linear)	• Ratings of quality of food, décor and service ratings (Zagat) • Michelin star/s awarded • Bib Gourmand awarded

The proliferation of electronic word of mouth (e-WOM) – enabled by the emergence of numerous online consumer review (OCR) websites and platforms devoted to consumer networking – overcame the inherent limitations of traditional WOM. This considerably facilitated potential patrons' ability to access information and contribute to information sharing. A number of studies have not only accounted for the ever-increasing role of e-WOM as a primary source of information for consumers in the hospitality and restaurant industries but have also linked positive digital reviews to establishments' reputation and revenues (Luca, 2011; Kim *et al*., 2016).

These considerations call for new research that extends the geographical scope of analysis and compares the impact of expert and consumer evaluations on pricing in more homogeneous segments of the restaurant market. To this effect, our study contributes by exploring the determinants of menu pricing in the top segment of the restaurant sector in Italy and estimating the influence of both experts (represented by Michelin and Gambero Rosso) and consumers (represented by individuals' reviews posted on TripAdvisor). A similar comparative approach has been applied to other sectors such as the wine (Oczkowski and Pawsey, 2019) and film (Peng *et al*., 2013) industries.

3 – Data and methodology

3.1 – *Data description*

The data sample is comprised of 372 restaurants in Italy that were awarded one or more Michelin stars in 2020 and so featured in that year's edition of the Michelin Guide (2022). The total number of chosen restaurants is depicted in Table 2. The Guide is considered the highest international culinary authority, honouring merit in culinary skill and gastronomic expertise in the form of Michelin stars: one star for 'High quality cooking, worth a stop'; two stars for 'Excellent cooking, worth a detour' and three stars for 'Exceptional cuisine, worth a special journey'. Moreover, the Guide provides short descriptions of featured establishments and their cuisine styles and assigns a fork and spoon symbol rating (ranging from 1 to 5) for dining experience, ambiance, décor, table setting and service quality. The exiguous number of Michelin-starred restaurants speaks to its exclusivity; starred restaurants represent the uppermost tier of the restaurant market, providing not only exceptional food but also a remarkable dining experience, pleasant ambiance, and highly professional service.

Table 2 – Michelin-starred restaurants in Italy, in 2020 (Source: authors' elaborations on data gathered from the Michelin Guide 2020)

	One Star	*Two Stars*	*Three Stars*	*TOTAL*
N° Restaurants	326	35	11	**372**
%	87.64	9.40	2.96	**100**

Different measurement variables were gathered for each establishment, using an array of sources that included specialised guidebooks published by the Michelin Guide (Michelin, 2019) and Gambero Rosso (AA.VV, 2019), online platforms (TripAdvisor) and the websites of the restaurants included in our sample. An overview of the complete set of variables, grouped according to the type of information provided and supplemented by the relative source, can be found in the appendix (Table A1) along with corresponding descriptive statistics (Tables A2 and

A3). The set of variables includes the dependent variable (PRICE) and the following regressors believed to affect price (hypothesised on the basis of the reviewed literature): number of Michelin stars (STARS); comfort level (COMFORT and RED); cuisine style (STYLE); Gambero Rosso scores for service and cellar (GR_SERVICE and GR_CELLAR); macro-region (REGION) as well as the context (i.e. urban, rural or metropolitan) in which an establishment is situated (CONTEXT); control variable for restaurants located within hotels (HOTEL); restaurant capacity represented by number of available seats (SEATS); the option of a fully vegetarian menu (VEG); TripAdvisor global scores as well as scores for cuisine, service, quality–price ratio (TA_AVG, TA_CUISINE, TA_SERVICE and TA_QP); number of reviews on TripAdvisor (N_REV) and the availability of certain amenities, namely outdoor dining, private tables, a garden and carpark (OUT_DIN, PRIV_TAB, GARDEN and CAR_PARK).

The data collection process took place between May and June 2020. While information drawn from guidebooks is not susceptible to intra-year variations (because they are updated and reissued annually), TripAdvisor ratings may alter whenever a new review is added. However, since data collection occurred during a period of scarce or even null activity as a result of forced restaurant closures due to national COVID-19-related restrictions and lockdowns, the time lag between the beginning and end of the data collection process can be ignored.

In regard to the dependent variable (PRICE), an individual proxy of each establishment's actual prices must be determined, as although restaurants apply fixed prices to menu items, customer spending differs according to personal considerations such as preferences, attitudes and budget constraints. Although some previous studies opted for measures such as average check (Susskind and Chan, 2000) or average price (Fogarty, 2012; Yim *et al*., 2014), our study adopted a different strategy to suit its focus on the top segment of the restaurant industry. The Michelin Guide indicates the price level of each reviewed restaurant, thus providing readers with a price range within which the given values represent minimum and maximum expenditure for set menus, beverages and other items not featured in the menu which include service, cover, extras (e.g. coffee or extra ingredients), etc. Hence prices provided by the Michelin Guide refer to tasting menu prices, typically the least and most expensive. In the rare case that a Michelin-starred restaurant does not offer a tasting menu, the upper price refers to the cost of a meal comprised of entrée, first course, main dish and dessert. Given that the upper bound of the price range reported by Michelin is an accurate proxy of the cost of a complete menu in a restaurant (wine and beverages excluded), it seems viable to use that as the dependent variable.

In order to obtain more precise information, we checked the website of each restaurant to verify the price of the most expensive tasting menu. We then compared the price advertised on the restaurant's website (where available) to the upper bound price stated by the Michelin Guide. Most of the restaurants in the dataset (314 out of 372, corresponding to 84.4 per cent) provided tasting menu prices on their websites. The correlation coefficient between the upper price bound reported by the Michelin Guide and the actual price retrieved via restaurant websites is 0.8802, which proves that the Guide provides accurate price information for reviewed establishments. Unfortunately, 34 establishments had to be removed from our study sample due to insufficient data. Of these excluded restaurants, 33 held one Michelin star, while only one missing restaurant boasted two stars. No three-starred restaurants were excluded from the dataset. Therefore, missing data reduced the sample dimension from the original 372 restaurants to 338 restaurants eligible for analysis.

3.2 – *Hypotheses and general model specification*

Drawing on the findings of previous studies, the expected evidence of the effect on price, exerted by variables already accounted for in existing research, was used to formulate the respective hypothesis. Conversely, new predictors (e. g. TripAdvisor evaluations) are tested against a hypothesis of the kind 'no effect expected'. The same hypothesis applies either when results of previous research are contradictory for similar variables or when variables are not considered strictly comparable across different studies.

Table 3 – Research hypotheses

HYPOTHESIS	VARIABLE	RESEARCH	EXPECTED EFFECT
1a, 1b and 1c	Expert ratings for food (1a), service (1b) and setting (1c)	Snyder and Cotter (1998), Gergaud *et al*. (2010) and Shin (2018)	Positive
2	TripAdvisor ratings	-	No effect
3	Cuisine style	Fogarty (2012) and Yim *et al*. (2014)	Non-comparable → No effect
4	Hotel	Gergaud *et al*. (2010)	Positive
5	Seats	Fogarty (2012)	Non-comparable → No effect
6a	Private rooms	Fogarty (2012) and Yim *et al*. (2014)	Positive Negative → No effect
6b	Outdoor dining	Fogarty (2012)	Negative
6c	Parking	Yim *et al*. (2014)	Positive
7	Region	-	No effect
8	Context	-	No effect

Qualitative predictors require dichotomous coding in order to be used in regression analysis. In particular, for the multi-outcome nominal predictors – i.e. STARS, COMFORT, REGION, CONTEXT and STYLE – applying dummy coding allowed us to obtain individual regression coefficients for single outcomes. In contrast, predictors such as RED or HOTEL are, by their nature, expressed as dummy variables. In order to establish a baseline for the interpretation of dummy variables for REGION, CONTEXT and STYLE, the selection was performed by comparing average prices for each of the possible outcomes by the means of One-Way ANOVA. The outcome with the highest average price was set as the baseline (Galati *et al*., 2017). This process led to the selection of CENTER, METROPOLITAN and CREATIVE as references for the respective variables.

A different logic was applied for measuring Michelin stars (STAR_1, STAR_2 and STAR_3). Since the majority of establishments had been awarded one star, and since this represents the entry level for achieving stars, STAR_1 was selected as the reference category for interpreting the results. The same applies for comfort, where COMF_LOW was set as the category baseline. For all other dummy factors (RED, HOTEL, VEG_MENU, OUT_DIN, PRIV_TAB, GARDEN and CAR_PARK), the natural baseline was represented by 0 (underlying attribute not present).

Conforming with past research, OLS regression was used to analyse the data (Yim *et al.*, 2014). In its most basic (linear) form, hedonic price modelling is generally expressed as the following equation:

$$Predicted\ price = f(Xi) \qquad [1]$$

where Xi is the vector of variables hypothesised to affect pricing [x_1, x_2, x_n], as listed above and in more detail in Table A1 (see Appendix). Relating the general expression to the present case, the linear hedonic pricing equation took the form:

$$P = f(\mathit{STARS, COMFORT, RED, GAMBERO\ ROSSO, N\_REV, TRIPADVISOR, SEATS, HOTEL, VEG,}$$
$$\mathit{AMENITIES, CONTEXT, REGION, STYLE}) \qquad [2]$$

3.3 – *Model selection*

Once the basic equation was defined, the OLS regression was first tested for the linear model. Then, in keeping with previous studies (see Yim *et al.*, 2014), a log-linear transformation on the dependent variable was performed. The log-linear functional form, in virtue of its ability to normalise skewed distributions (Osborne, 2010; Benoit, 2011), is highly popular in hedonic price modelling for restaurants (Gergaud *et al.*, 2007; Fogarty, 2012; Yim *et al.*, 2014; Shin, 2018), although it prevents straightforward interpretation of coefficients.

The linear model (Model [1]) was tested by entering PRICE as the dependent variable and the entire set of predictors as independent variables. Thirteen predictors were found to be significant at the five per cent level, whereas four were significant at the 10 per cent level. As far as collinearity is concerned, the VIF statistic was lower than 10 for all 28 predictors. Therefore, collinearity did not present as an issue for the studied sample. Casewise diagnostics indicated the presence of three observations with standardised residual values higher than the conventional value of 3. In this specific case, for all three, the model produced a considerably lower predicted value with respect to actual price. In order to exclude the presence of heteroskedasticity, the Breusch–Pagan (BP) and Koenker tests were performed. For both tests, the null hypothesis assuming homoskedasticity was accepted (BP: 0.051; Koenker: 0.264), and constant variance of residuals was assumed. Finally, the normality of standardised residuals was assessed by means of the Shapiro–Wilk test. The p-value (0.0001) induces to reject the null hypothesis, suggesting that residuals could significantly deviate from a normal distribution.

As a result of the contradiction of the normality (of residuals) assumption, and in continuity with past research in the hospitality industry (Zhang *et al.*, 2011; Yim *et al.*, 2014), logarithmic transformation on the dependent variable was then performed (Model [2]). Although the R^2 and adjusted R^2 values decreased slightly, other indicators showed that the transformation improved the accuracy of the model. Upon inspection, in contrast to the linear model, no standardised residual fell outside +/-3 standard deviations from the mean. The results of the Shapiro–Wilk normality test confirmed that residuals are normally distributed (Shapiro–Wilk Sig. = 0.955). Again, the BP and Koenker tests suggested that heteroskedasticity was not an issue for the data analysed, with the BP test improving with respect to the linear model (significance level increased from a borderline value of 0.051 to a more satisfying 0.133).

In the log-linear model, the number of significant regressors at a five per cent threshold increased to 14 variables, while three regressors were found to be significant at the 10 per cent level. Moreover, the model constant is still significant (Sig. = 0.000; b_0 = 4.407). In light of the above, the log-linear model was selected and took the following final form:

$$ln\ P_i = \alpha + \sum_n^N \beta_n X_{n,i} + \varepsilon_i \quad [3]$$

In order to overcome the above-mentioned issue related to the interpretation of logarithmic coefficients, we drew on Galati *et al*. (2017) in applying the Kennedy method (1981), as expressed by the formula below, to obtain the percentage impact of dummy predictors on pricing, where β is the individual dummy standardised coefficient, and V is the squared standard error of β:

$$\Delta P\ per\ cent = \left\{\exp\left[\beta - \frac{1}{2}V(\beta)\right] - 1\right\} * 100 \quad [4]$$

4 – Results and discussion

4.1 – *Results*

Results are reported in Table 4. Michelin ratings for food, comfort and ambiance, in addition to Gambero Rosso ratings for service, as well as the variable accounting for restaurants being located within hotels, were shown to positively impact pricing, as the respective standardised coefficients are all positive and widely significant. Conversely, TripAdvisor quality–price ratio scores, number of seats, availability of private tables, restaurant context, restaurant geographical location and cuisine styles all have negative coefficients. In particular, for CONTEXT, REGION and STYLE, the negative coefficients associated to the predictors trace back to the baseline selection strategy.

Table 4 – Hedonic price model (regression results)

VARIABLE	B Estimate	Std. Error	BETA	p-value	Price impact (%) (Kennedy transf.)
(Constant)	4.525	0.364	-	**0.000*****	
STARS					
STAR_1	-	-	-	-	-
STAR_2	0.266	0.048	0.247	**0.000*****	27.87
STAR_3	0.564	0.084	0.310	**0.000*****	35.86
COMFORT					
COMF_LOW	-	-	-	-	-
COMF_MED	0.084	0.030	0.130	**0.006*****	13.83
COMF_HIGH	0.151	0.055	0.154	**0.006*****	16.47
RED					20.15
GAMBERO ROSSO					
GR_SERVICE	0.044	0.013	0.209	**0.001*****	-
GR_CELLAR	-0.012	0.016	-0.042	0.460	-

TRIPADVISOR					
TA_AVG	0.016	0.079	0.012	0.844	-
TA_CUISINE	-0.069	0.076	-0.054	0.362	-
TA_SERVICE	0.047	0.071	0.038	0.505	-
TA_QP	-0.111	0.059	-0.114	**0.062***	-
N_REVIEWS	0.000	0.000	0.008	0.855	-
SEATS	-0.002	0.001	-.0111	**0.011****	-
HOTEL	0.119	0.032	0.162	**0.000*****	17.53
AMENITIES					
VEG	0.020	0.038	0.021	0.586	-
OUT_DIN	-0.023	0.027	-0.035	0.406	-
PRIV_TAB	-0.053	0.028	-0.077	**0.058***	-7.45
GARDEN	-0.022	0.034	-0.029	0.514	-
CAR_PARK	-0.037	0.031	-0.057	0.235	-
CONTEXT					
Metropolitan	-	-	-	-	-
Urban	-0.122	0.045	-0.161	**0.007*****	-14.96
Non-urban	-0.132	0.044	-0.197	**0.003*****	-17.96
REGION					
Centre	-	-	-	-	-
Northwest	-0.079	0.036	-0.113	**0.028****	-10.74
Northeast	-0.023	0.039	-0.030	0.559	-
South and islands	-0.076	0.038	-0.100	**0.047****	-9.58
STYLE					
Creative	-	-	-	-	-
Modern	-0.052	0.029	-0.078	**0.077***	-7,.4
Regional	-0.113	0.047	-0.104	**0.017****	-9.98
Seafood	-0.042	0.059	-0.029	0.474	-
Other	-0.167	0.061	-0.109	**0.007*****	-10.49
Model: log-linear with forced entry R: 0.756 R^2: 0.572 Adjusted R^2: 0.533 ANOVA Sig.: 0.000					

For example, since the CONTEXT baseline is 'Metropolitan', the negative coefficients for 'Urban' (-0.161) and 'Non-urban' (-0.197) must be interpreted as the expected impact on pricing for a restaurant located in urban or non-urban contexts, with respect to restaurants based in metropolitan locations. The same applies to cuisine styles and the geographical location of restaurants. According to the results, restaurants that serve creative cuisine are able to charge higher prices, on average and other factors being equal, while restaurants located in northwest, south and island regions charge, on average, lower prices compared to establishments in central regions. Finally, the remaining variables were all found not to be significant predictors of restaurant prices in the specific market segment considered.

4.2 – *Discussion*

While the main question guiding our analysis – Does consumer opinion, compared to expert opinion, affect price determination in the restaurant industry? – is mainly answered by testing hypotheses H1a, H1b, H1c and H2, the results discussed below also include the other hypotheses reported in Table 3. This renders our results comparable to the findings of previous studies, thus contributing to a broader and more nuanced understanding of restaurant price determination.

H1a: *Expert ratings of food positively affect price determination:* → *ACCEPTED.*

In an array of studies that applied the hedonic pricing model in assessing the impact on pricing of being awarded one or more Michelin stars, a strong positive relationship always emerged (Gergaud *et al*., 2007; Gergaud *et al*., 2010; Shin, 2018). Others, such as Fogarty (2012), have investigated the impact on prices of food ratings sourced from different gastronomic guides, and they came to the same conclusion. Unsurprisingly, our research confirms and reinforces the theory that the more Michelin stars an establishment holds, the higher the price they charge to customers (+27.87 per cent for two stars and +35.86 per cent for three stars). Among the studied variables, expert ratings of food exert the strongest positive influence on price.

H1b: *Expert ratings of service quality positively affect price determination:* → *ACCEPTED.*

The impact of service quality on both consumers' willingness to pay and their satisfaction levels has been the subject of numerous studies (see Homburg *et al*., 2005; Njite *et al*., 2008). Highly competent and professional service is crucial in the upper segment of the restaurant and dining industry where, as Kiatkawsin and Han (2019) discovered, gastronomic and emotional involvement plays a fundamental role in consumers' willingness to pay premium prices for unique experiences. Moreover, Snyder and Cotter (1998) found that Michelin-starred restaurants are consistently able to raise prices to meet the increased costs associated with improved service quality. Similarly, in our results, expert ratings of service quality show a strong positive association with price.

H1c: *Expert ratings for setting positively affect price determination:* → *ACCEPTED.*

The importance of setting within service industries has garnered extensive academic interest (see Booms and Bitner, 1982). Restaurants not only provide food, but they also function as sites of consumption; and so, setting, ambiance and décor strongly influence patrons' dining experience. In line with Gergaud *et al*. (2010), our study confirms that favourable expert ratings for setting exert a strong, positive influence on price.

H2: *TripAdvisor ratings (e.g. average score, cuisine, service and quality–price ratio scores) do not affect price:* → *ACCEPTED.*

Contrary to past research that found that customer-based ratings provided through Zagat positively influenced pricing (Susskind and Chan, 2000; Yim *et al*., 2014), our study does not reach the same conclusion. That is, we observe no significant effect on pricing caused by cuisine, service and average ratings in TripAdvisor. Only the quality–price ratio expressed by TripAdvisor users presents a statistically significant relationship with price, with higher prices being associated with lower scores. TripAdvisor users thus demonstrate high price-sensitivity and tend to award higher ratings to Michelin-starred restaurants that provide excellent food for a price perceived as fair. There are two possible reasons for this divergence from previous findings. First, there is a substantial difference between Zagat and TripAdvisor in terms of accessibility: the latter is a completely open-access platform, while the former controls for the number and quality of its reviewers. Second, restaurants reviewed through Zagat constitute a more homogeneous subgroup of the restaurant market, while TripAdvisor is a far more comprehensive collector, indiscriminately applying a universal five-point scale to three-starred Michelin restaurants and street food vendors alike.

H3: *Cuisine style does not affect price determination:* → REJECTED.

Our results indicate that cuisine style exerts a statistically significant influence on the prices charged by Michelin-starred restaurants in Italy. A high premium is placed on creative cuisine, while 'Other', 'Modern' and 'Regional' cuisines are associated with statistically significant lower average prices (between -10.5 per cent and -7.5 per cent, approximately). This finding appears to be consistent with Michelin's self-declared capacity to promote creativity and individuality in the restaurant industry, as well as the findings of Surlemont at el. (2005) and Balasz (2001), according to which creativity is considered essential by Michelin-starred chefs themselves. Moreover, as was observed by Ottenbacher and Harrington (2007), who studied the innovation processes of Michelin-starred chefs, creativity constitutes a strategy to generate competitive advantage, which, in turn, drives differentiation and the capacity to charge premium prices.

H4: *Being part of a hotel positively affects price determination:* → ACCEPTED.

It is not unusual for Michelin-starred restaurants to be located within premises such as hotels and resorts. Indeed, of the 338 establishments included in our sample, 89 were accommodated within hotels and similar sites. Only one existing study has assessed the effect on pricing of a restaurant located within a multi-faceted hospitality structure, and a small price premium (around 4.6 per cent) was found to be associated with placement (Gergaud *et al*., 2010). The hedonic pricing model adopted in this study shows that a substantial premium is incurred for restaurants located within hotels and resorts (+17.53 per cent). This could be due to the fact that, in most instances, Michelin-starred restaurants belong to luxurious four- or five-star hotels managed by international corporations. It then comes as no surprise that such restaurants are able to command high prices, not only as a consequence of their status as providers of exceptional food but also because of the luxurious settings in which they are located.

H5: *Restaurant capacity (expressed by the number of available seats) does not affect price:* → REJECTED.

Of previous studies, only Fogarty (2012) included a variable to account for the effect of restaurant capacity on price. He found that up to a certain threshold, restaurant meal prices increased in tandem with an establishment's capacity, at which point they then began to decrease. This was probably due to the broad variability of capacity in his sample, where the number of seats ranged between 14 to 800 units. A similar effect is unlikely in instances where capacity has a far narrower range, as is the case in our study. Indeed, our results show that the SEATS coefficient is negative and highly significant, revealing that increased capacity is associated with diminished prices.

H6a: *Availability of private dining rooms does not affect price determination:* → REJECTED.

Contrary to Fogarty's (2012) findings, our study found that the availability of private dining rooms has a statistically significant negative effect on price. An explanation could be linked to restaurant size, as establishments that offer private dining options are likely to be larger than those that do not provide such amenities. From a quick comparison of average seating capacity, grouped on the basis of private tables available, it emerges that restaurants that offer private dining can rely on a higher number of seats. Considering that increased capacity is associated with lower prices, the negative premium for restaurants offering private tables can be partially explained. This finding is in line with Yim *et al*. (2014).

H6b: *Availability of outdoor dining options negatively affects price:* → REJECTED.

Contrary to Fogarty's (2012) study that identified a statistically significant negative association between price and outdoor dining, our study arrived at a different result, namely that the related coefficient was not statistically significant.

H6c: *Parking availability positively affects price:* → REJECTED.

The availability of parking facilities is particularly important for restaurants located in urban and metropolitan areas. Indeed, Yim *et al*. (2014) found a very strong positive relationship between parking availability and price for restaurants in Seoul. However, the scope of our investigation encompassed all of Italy, and so, parking availability is not seen to exert any influence on price.

H7: *Regional context (as expressed by Italian macro-regions) does not affect price:* → REJECTED.

Other factors held constant, restaurants located in north-western and southern regions tend to charge lower prices, on average, than their competitors in central regions. This can likely be explained by the lower density of starred establishments in central Italy with respect to the northwest, their contextual concentration in highly attractive touristic cities crowded by high-spending foreigners, and the different purchasing power between central and southern regions.

H8: *The context (non-urban, urban and metropolitan) of an establishment does not affect price:* → REJECTED.

Our results indicate that the coefficients for both non-urban and urban locations are highly significant, indicating a strong relationship with price. Their sign is negative, meaning that meal prices in non-urban and urban establishments are significantly cheaper than their metropolitan counterparts (other factors held constant), which likely incur substantially higher fixed costs. It should be noted that being situated in a non-urban or urban location negatively impacts price more than any other predictor (-17.96 and -14.96 per cent, respectively).

5 – Conclusions

Drawing on the theoretical framework of HPA, this paper casts light on factors affecting price determination in fine-dining restaurants, by focusing on Michelin-starred restaurants in Italy. In particular, it compares the impact of gastronomic guides and online consumer-based evaluation platforms on the determination of menu prices. In keeping with previous studies, expert critique on food, service and setting is proven to exert a strong, positive impact on product price. On the contrary, user-based ratings, expressed as scores obtained through TripAdvisor, are generally found not to be significant determinants of price. Among other relevant price determinants, such as context and size, the results of our study indicate that creative cuisine attracts premium pricing compared with other cuisine styles. This confirms the eminent role that creativity and Michelin-starred chefs, in particular, play in generating new economic value (Cerisola, 2019; Batat, 2021).

The results of this study contribute to the economic literature on price determination in hospitality and creative industries. As such, they may inform restaurant operator and consumer choice within the field of hospitality and gastronomic tourism. However, conclusions cannot be generalised beyond the scope of this study, and so further research is necessary. By focusing exclusively on Michelin-starred restaurants, we were able to reduce our analysis to a relatively homogeneous segment of the market in which the role and opinion of experts is widely recognised, thus facilitating data collection across an entire country and containing issues associated with empirical heterogeneity. However, this exclusive focus prevents conclusions from being extended to other market segments in which the role of expert evaluation on price determination may be less impactful. This warrants further investigation.

Moreover, our analysis of user-based evaluations is limited to scores posted on TripAdvisor. As such, although the TripAdvisor platform currently represents one of the most exhaustive databases for the collection and dissemination of consumer opinion in the travel and hospitality sectors, the robustness of our findings could be further verified by investigating and comparing the role played by other user-based platforms (such as Zagat and Google Reviews), which present different features in terms of accessibility and coverage. Finally, while this study is exceptional in that its scope accounts for an entire country, similar analyses on other countries and regions should be carried out so as to individuate more general patterns relating to the influence of expert versus consumer evaluations on restaurant pricing.

6 – References

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APPENDIX

Table A1 – Description of variables

VARIABLES	SOURCE	DESCRIPTION
GENERAL INFORMATION		
PRICE	Michelin Guide (2020) and restaurant websites	Price of a complete tasting menu.
REGION (*Northwest; Northeast; Centre; South and islands*)	Michelin Guide (2020)	Categorisation follows the NUTS 1 scheme applied by Eurostat. However, the NUTS 1 scheme distinguishes between the 'South' and 'Islands', whereas this study aggregated the two regions for methodological reasons.
CONTEXT (*Non_Urban; Urban; Metropolitan*)	Authors' elaboration	Indicates location. The 'Metropolitan' variable was assigned to restaurants located in Rome, Milan, Turin and Naples; the 'Urban' variable was assigned to restaurants located in Italian cities with a

		population greater than 30,000 (excluding the abovementioned metropolises).
HOTEL (*No; Yes*)	Websites, Gambero Rosso guidebook (2020)	Dummy variable that assumes a value of 1 if a restaurant is situated within a hotel or resort.
SEATS	Gambero Rosso guidebook (2020)	Restaurants that offer rooms for overnight stay were not coded as hotels. Number of available seats.
MICHELIN		
STARS (*STAR1; STAR2; STAR3*)	Michelin Guide (2020)	Number of Michelin stars awarded.
COMFORT (*COMF_LOW; COMF_MED; COMF_HIGH*)	Michelin Guide (2020)	Comfort level, represented as a Forks and Spoons rating by the Michelin Guide. Comfort is impacted by a restaurant's environment/situation, setting, ambiance and service, etc. Since only five and three establishments were awarded one and five Forks and Spoons, respectively, the COMFORT variable was recoded for regression analysis purposes into three dummy variables representing 'low' (one or two Forks and Spoons), 'medium' (three Forks and Spoons), and 'high' (four or five Forks and Spoons) comfort levels.

RED (*No; Yes*) CUISINE STYLE (*Creative; Modern; Regional; Seafood; Other*)	Michelin Guide (2020) Michelin Guide (2020)	Variable assumes a value of 1 whenever a venue was considered to be particularly pleasant, according to the Michelin Guide. Cuisine style, as indicated by the Michelin Guide. The category 'Regional' includes typical cuisines from the peninsula (e.g. local cuisine from Abruzzo or Emilia), whereas 'Other' comprises residual styles, such as classic cooking, country cooking and French and Japanese cuisine, etc.
TRIPADVISOR TA_AVG TA_CUISINE TA_SERVICE TA_QP N_REV	 TripAdvisor website TripAdvisor website	 TripAdvisor scores for both individual attributes and the average restaurant score. Scores range between 0 and 5, with 0.5 increments. TripAdvisor scores for both individual attributes and the average restaurant score. Scores range between 0 and 5, with 0.5 increments.
AMENITIES VEG OUT_DIN PRIV_TAB GARDEN CAR_PARK (*No, Yes*)	 Michelin Guide (2020)	 Group of individual dummy variables that assume a value of 1 if the underlying attribute is present.

GAMBERO ROSSO GR_SERVICE GR_CELLAR	Gambero Rosso guidebook (2020)	Gambero Rosso ratings for service (0–30 scale) and cellar (0–20 scale).

Table A2 – Absolute and percentual frequencies for qualitative variables

	FREQUENCY	FREQUENCY %
MICHELIN STARS		
1 star	293	86.7
2 stars	34	10.1
3 stars	11	3.3
CONTEXT		
Non-urban	211	62.4
Urban	81	24.0
Metropolitan	46	13.6
REGION		
Northwest	102	30.2
Northeast	82	24.3
Centre	74	21.9
South and islands	80	28.1
CUISINE STYLE		
Creative	141	41.7
Modern	130	38.5
Regional	22	9.8
Seafood	18	5.3
Other	16	4.7
COMFORT		
Quite comfortable	5	1.5
Comfortable	107	31.7
Very comfortable	184	54.4
Top-class comfort	39	11.5
Luxury	3	0.9
HOTEL		
Independent	249	73.7
Hotel	89	26.3
VEGETARIAN MENU		
No	295	87.3
Yes	43	12.7
RED		
No	202	59.8
Yes	136	40.2
OUTDOOR DINING		
No	139	41.1
Yes	199	58.9

PRIVATE TABLES		
No	222	65.7
Yes	116	34.3
GARDEN		
No	257	76.0
Yes	81	24.0
CARPARK		
No	182	53.8
Yes	156	46.2

Table A3 – Descriptive statistics for quantitative variables

	Mean	S.D.	Range	Min	Max
PRICE	126.44	43.957	250	50	300
SEATS	39.15	17.266	138	12	150
N° REVIEWS	523.27	451.953	3510	18	3528
TA_AVG	4.46	0.249	1.5	3.5	5
TA_CUISINE	4.53	0.255	1.5	3.5	5
TA_SERVICE	4.49	0.260	1.5	3.5	5
TA_QP	4.40	0.332	2	3	5
GR_SERVICE	24.74	1.553	8	21	29
GR_CELLAR	16.20	1.124	6	13	19