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# The STAR WARS of Michelin Guide restaurants: a wine list perspective – a case study from Italy

Riccardo Saracino
*Department of Agricultural and Environmental Sciences – Production, Landscape, Agroenergy, University of Milan, Milan, Italy, and*

Stefano Corsi and Chiara Mazzocchi
*University of Milan, Milan, Italy*

## Abstract

**Purpose** – This study aims to examine how restaurant features, particularly wine list elements like prices and origins, influence ratings for Michelin Guide restaurants.

**Design/methodology/approach** – Data from 555 Italian Michelin Guide restaurants were collected from the Michelin Guide website, TripAdvisor and online wine lists. Ordinary least squares regression was used to evaluate the impact of restaurant attributes on ratings.

**Findings** – Customers assign higher ratings to restaurants with specific features. A positive correlation exists between food menu prices and ratings, except for extremely high-priced restaurants, which show a negative effect. Online exposition shows a positive effect on rating. Restaurants with higher price ranges and more Michelin stars (1, 2 or 3) also receive better ratings. Notably, establishments with lower median wine list prices tend to achieve higher ratings, except for top-tier price restaurants, where the effect on ratings is positive. Furthermore, restaurants offering too many local wines may see a decline in ratings.

**Research limitations/implications** – The analysis focuses on Italian Michelin Guide restaurants and excludes specific location or sales data.

**Practical implications** – Insights into wine list pricing and diversity can help managers refine offerings and pricing strategies to enhance customer satisfaction and improve ratings.

**Originality/value** – This study highlights how wine list characteristics impact customer ratings and uncovers a non-linear relationship between food and wine prices and customer preferences.

**Keywords** Italy, Wines, Regression, Restaurants, Econometric model, Michelin Guide, Wine list

**Paper type** Research paper

## 1. Introduction

There has been a growing interest in recent years in understanding the factors contributing to a restaurant's success in the upscale dining sector, including wine lists. Among the key factors influencing customer satisfaction and restaurant ratings in this sector, the most relevant include the overall dining experience, pricing, location and wine list (Barrera-Barrera, 2023). Although upscale restaurants hold a relatively small share of the market, haute cuisine and haute cuisine Guide are interesting under several perspectives, for instance



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in terms of reputation and financial performance (Surlemont and Johnson, 2005; Surlemont *et al.*, 2005). Along with creativity, haute cuisine also acts as a catalyst for cultural values and innovation (Filieri and Mariani, 2021; Albors-Garrigos *et al.*, 2013).



The Michelin Guide is one of the most internationally recognised standards for assessing restaurant quality and dining experiences. Currently, Italy ranks second worldwide for the number of Michelin-starred restaurants (Michelin Guide, 2024a, 2024b), renowned for seamlessly blending tradition and innovation in fine dining. Consequently, Italy has emerged as a global leader in the upscale restaurants scenario. While food quality remains a critical component, other aspects of the dining experience, particularly pricing strategies, can significantly impact a restaurant's rating. Thus, for restaurant owners and managers, understanding the relationship between price and customer satisfaction in relation to willingness to pay is important for establishments in the luxury sector (Kiatkawsin and Han, 2019). Moreover, wine list is a relevant tool in fine dining restaurants (Gergaud *et al.*, 2024), especially, because it is a key revenue driver, particularly through mark-ups (Livat and Remaud, 2018).

This study aims to assess the impact of various characteristics of upscale restaurants − including their features and wine lists − on overall ratings. Moreover, as previously mentioned, Italy is one of the most represented nations in the Michelin Guide − ranked as the second most awarded country worldwide − offering a valuable context and providing a case study holding significant relevance. The model applied here could also be adapted and extended to other countries with a similar status in the global culinary landscape, with appropriate adjustments to account for specific contextual factors, such as differing culinary traditions.

Although this model was developed using data from fine dining restaurants, particularly those listed in the Michelin Guide, it can also be applied to other types of restaurants. Fine dining establishments were chosen because relevant data (such as online wine lists) readily available online. However, many of the concepts and values found in upscale dining are transferable to other restaurant formats, since the elements used in this model are common across different restaurant categories. Those elements result in a model particularly suitable for replication within the fine dining sector, where the wine list plays a role in shaping customer satisfaction. At the same time, they are also relevant in more casual settings restaurant (e.g. restaurant not included in the Michelin Guide), especially in regions characterised by high levels of wine production and consumption.

This article is structured as follows. The literature review is divided into four sections: Section 2.1 examines existing research on haute cuisine and fine dining, highlighting the key factors that shape a restaurant's reputation and success. Section 2.2 focuses on online ratings and reviews, analysing their determinants and their impact on consumer behaviour. Section 2.3 explores the importance of wine lists, assessing how wine selection and presentation contribute to the dining experience and influence restaurant ratings. Section 2.4 presents the research questions guiding the study.

Following the literature review, Section 3 outlines the methodology. Section 4 presents the results, which are then discussed in Section 5. Finally, Section 6 concludes the paper with a summary of the main findings and implications.

## 2. Literature review

### *2.1 Michelin restaurants – upscale restaurants and fine dining*

The Michelin Guide features restaurants of exceptional quality. Among these, establishments that reach the highest standards are awarded one to three stars, based on a rigorous assessment framework encompassing five universal criteria: the quality of ingredients, mastery of flavour and cooking techniques, the chef's unique personality reflected in the cuisine, harmony of flavours and consistency across visits (Michelin Guide, 2024a, 2024b). Earning a Michelin star significantly elevates a restaurant's prestige and often leads to a marked increase in customer interest (Chiang and Guo, 2021).

Although still relatively limited, academic research on Michelin-starred restaurants spans a diverse range of topics, including the creative processes behind haute cuisine and the strategic management of these elite establishments (Vargas-Sanchez and López-Guzmán, 2020). The digital presence of Michelin-rated restaurants has also received scholarly attention, with studies exploring website management (Daries *et al.*, 2018), narrative strategies and visual design (Montargot *et al.*, 2022), as well as the role of social media in shaping brand identity (Fissi *et al.*, 2022). A growing area of interest focuses on sustainability in fine dining, particularly how high-end restaurants incorporate local sourcing and environmentally responsible practices into their offerings (Batat, 2020).

Moreover, within the luxury dining sector, research on service excellence underscores its importance in creating strong emotional bonds with guests (Panchapakesan *et al.*, 2022), while studies on consumer behaviour highlight the key factors that influence guests' willingness to pay premium prices for exclusive experiences (Kiatkawsin and Han, 2019). Notably, Michelin-starred restaurants also tend to invest more in extensive and curated wine lists compared to their non-starred peers (Gergaud *et al.*, 2014).

Notably, some case studies on Michelin restaurant only have been conducted already, both in Europe as in Germany (Harrington *et al.*, 2013) and Italy (Pangrazi *et al.*, 2022), and in Asia (e.g. Henderson, 2017; Nguyen and Dao, 2024).

### *2.2 Platform user-generated rating, reviews and restaurant features*

Online ratings are increasingly recognised as key indicators of restaurant reputation (Luca and Reshef, 2021). Despite their growing relevance in the hospitality industry, studies that treat restaurant ratings as primary outcome variables remain relatively scarce. Much of the existing literature has instead used online ratings as explanatory variables, for example, to predict reservation volumes (Anderson and Magruder, 2012). This trend is especially prevalent in hospitality research, where ratings are frequently used to forecast consumer behaviour or business outcomes (Filieri and Mariani, 2021; Greenberg *et al.*, 2023; Luca, 2016; Derrien *et al.*, 2024). In contrast, only a limited number of studies have analysed online ratings as dependent variables, often applying text-mining methods to explore consumer sentiment (e.g. Büschken and Allenby, 2016; Gan *et al.*, 2016; Ganu *et al.*, 2013; Jia, 2018).

Previous research has demonstrated that a higher volume of consumer reviews increases user interest, enhancing the likelihood of visits to a restaurant's Web page (Zhang *et al.*, 2010). Online reviews have also been widely studied in relation to restaurant performance and public perception. Many studies drawing on TripAdvisor data have adopted text-mining approaches to examine general restaurant reviews (Clauzel *et al.*, 2019), as well as reviews specifically related to Michelin-rated establishments (Nguyen and Dao, 2024). Consumer feedback has further been analysed based on guest typology (e.g. local vs non-local), highlighting its significance in evaluating restaurant experiences (Pezenka and Weismayer, 2020). Similarly, the influence of expert ratings on consumer behaviour has attracted scholarly attention (Clauzel *et al.*, 2019).

Some studies have investigated the impact of review volume on overall ratings (Yoo and Suh, 2022), as well as its effect on restaurant revenue performance (Luca, 2016). Among other factors, price has been identified as central to customer satisfaction, particularly in its relation to perceived restaurant quality (Lee, 2013). For instance, Kim *et al.* (2022) found that price significantly influences satisfaction levels, while Luca and Reshef (2021) explored this dynamic in the context of price increases. However, other scholars have argued that price may not always be a decisive factor in customer satisfaction (Iglesias and Guillén, 2004).

In the context of luxury dining, several attributes have been proposed to define the customer experience, with research consistently noting that expectations tend to be higher in upscale settings (Yang and Mattila, 2016). According to Mathayomchan and Taecharungroj (2020), the importance of these attributes may also vary depending on the restaurant's stylistic positioning. The impact of Michelin stars on both restaurant performance and consumer perception has also been a subject of growing academic interest (Rita *et al.*, 2023; Yoo and Suh, 2022).

### *2.3 Wine lists*

Wine is a key element in many restaurants, contributing significantly to both the establishment's offerings and profitability. With a higher markup than food items, wine serves as a vital revenue stream for restaurateurs, prompting substantial investment in selecting attributes such as optimal price-value combinations and wine origin (Lockshin *et al.*, 2011). However, the complexity of wine as a product often creates a "perceived risk" for consumers during selection, making carefully curated wine lists even more important (Lacey *et al.*, 2009). Thus, effective wine curation is crucial not only for profit maximisation but also for enhancing the overall dining experience. Additionally, food and wine pairings play a significant role in both the restaurant atmosphere and wine list design (Terblanche and Pentz, 2019). The composition of a wine list significantly influences a restaurant's quality and customer satisfaction for wine pairing (Sirieix *et al.*, 2011). Beyond its role in revenue generation, wine also carries cultural significance and contributes to the restaurant's brand identity, leaving lasting impressions on patrons (Batat, 2020).

Upscale restaurants frequently use wine as a tool for business strategy differentiation (Berenguer *et al.*, 2009). Research on Michelin-starred restaurants reveals that the food menu and pricing significantly influence restaurant ratings, with patrons of high-end establishments often demonstrating a greater willingness to pay premium prices, even with substantial wine mark-ups (Barrera-Barrera, 2023; Livat and Remaud, 2018). A well-structured wine list can enhance perceptions of service quality, encourage repeat visits and drive positive word of mouth. Wine lists not only serve as a primary source of information for patrons but also function as a competitive differentiation strategy. An effective wine list design can target specific customer segments and drive wine sales, a critical component of restaurant revenue (Gil *et al.*, 2009). Additionally, a carefully curated wine list, focusing on internationality and variety, can increase customer satisfaction while enhancing the restaurant's perceived value and prestige (Ruiz-Molina *et al.*, 2010; Perla *et al.*, 2014). Researchers have analysed wine list attributes, including structure and pricing strategies, to optimise restaurant performance, which, in turn, may further influence customer satisfaction (Staub and Siegrist, 2022).

Pricing is a key determinant in consumer choice, particularly for wine in upscale restaurants. Characteristics of the wine list, such as the range and diversity of options, vary significantly depending on the establishment type and directly influence the customer experience (Gil Saura *et al.*, 2008). Studies suggest that moderate wine pricing can be a strength for restaurants, as excessively high prices may negatively affect customer satisfaction (Coqueret, 2015; Hsieh *et al.*, 2019), whereas higher prices are often associated with better quality (Schiessl, 2024). Further research underscores the importance of wine origin and grape variety as critical factors influencing consumer choices (Ruiz-Molina *et al.*, 2010; Bruwer *et al.*, 2012). Incorporating local wines into the menu can be a successful strategy, enriching the dining experience and fostering a connection to the locale (Čaušević and Nikolić, 2024; Sirieix *et al.*, 2011; Perla *et al.*, 2014). Local wines may enhance the dining experience in the tourism context by creating a sense of place and local identity, transforming meals into cultural events (Crespi-Vallbona and Mascarilla-Miró, 2020; Livat and Remaud, 2018).

### *2.4 Research questions*

By examining the factors discussed in previous sections, this research aims to provide valuable insights for restaurateurs looking to enhance their offerings to achieve higher ratings and maintain competitiveness in a crowded market. The findings of this study will offer practical guidance for restaurant owners and managers seeking to refine their business strategies in an increasingly competitive environment. To provide managers the practical implications, discussed in the last section of this article, this study relies on the assumption that this statistical model estimates the customer satisfaction, expressed as the restaurant rating, analysing the effect of restaurant features and especially the wine list elements.

This study seeks to address gaps in understanding how restaurant features, especially wine lists, influence online ratings. While the role of wine in enhancing the dining experience is increasingly recognised, limited research has examined the impact of wine selection, price range and other restaurant attributes on customer ratings. The goal is to provide actionable insights for restaurateurs aiming to optimise wine lists and other restaurant offerings to improve customer satisfaction and ratings. Starting with the hypothesis that wine list features impact restaurant ratings, this research is structured around the following three questions:

*RQ1.* How do online-sourced factors, along with intrinsic restaurant characteristics, influence Michelin restaurant ratings?

*RQ2.* What is the impact of receiving Michelin stars on restaurant ratings?

*RQ3.* How do the features of a wine list, in terms of price, diversity and wine origin, affect Michelin restaurant ratings?

## 3. Methodology

### *3.1 Conceptual framework and sampling*

Data for this study were sourced from the Michelin Restaurant website, TripAdvisor and various restaurant websites hosting wine lists. During the data collection phase in August 2024, a total of 2,029 restaurants listed on the Michelin Restaurant Italy website were identified, of which 555 provided accessible wine lists and menu details. The data set included information on star ratings, price ranges and restaurant locations. Additionally, TripAdvisor data on ratings, reviews and the presence of restaurants in the Top 10 were updated in October 2024. From the 555 restaurant websites, average menu prices and wine list characteristics were collected, leading to the extraction and analysis of 276,557 wines.

The distribution of Michelin restaurants and those included in this study is illustrated in Figure 1, which highlights their locations across the 20 Italian regions. Table 1 provides a detailed overview of each region, including the total number of restaurants as listed in the Michelin Guide, the number of Michelin-starred establishments, and a breakdown by star classification (with green-starred restaurants counted as one star). Additionally, the table categorises restaurants according to various price ranges used in the Michelin Guide: €(<€35), €€(€35–60), €€€(€60–100) and €€€€(> €100), offering insights into Italy's culinary landscape.

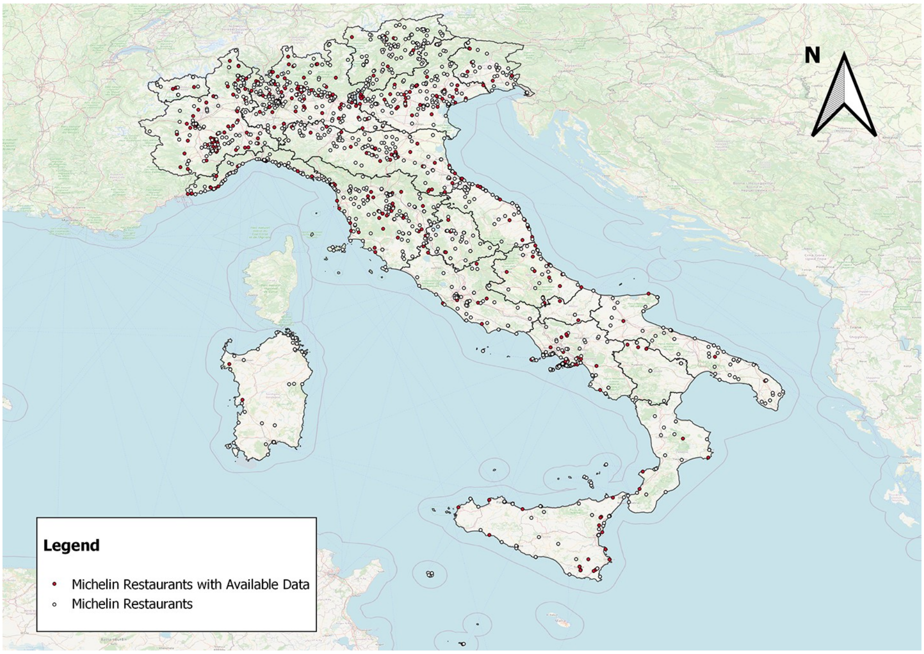


**Figure 1.** Italian Michelin restaurants

The TripAdvisor data refers to the 555 restaurants previously mentioned, providing key metrics such as the average rating, calculated as a weighted score (*RATING*), total review counts (*REVIEW*) and each restaurant's ranking within its local top ten (*TOP10*), constrained by administrative boundaries and the region in which the restaurant is located (*REGION*). Additionally, the Michelin Guide data includes each restaurant's price range (*PRICE_RANGE*) and the number of Michelin stars (*STAR*). The wine list data for these 555 restaurants includes important metrics such as menu pricing (averaged from tasting and fixed menus) (*MENU* and *MENU2*), wine pricing (median values to mitigate the influence of outliers) (*WINE_PRICE* and *WINE_PRICE2*) and the count of regional wines (*REG_WINE*), representing the number of wines from the restaurant's region. Furthermore, the diversity of wine origins was documented by noting the countries represented on each list (*WINES*). A threshold was applied to include only some countries present in the wine lists to avoid multicollinearity, as the most international wine lists tended to feature similar offerings of less common wines. A diversity index (*TYPOLOGY*), based on the Shannon−Wiener Index (Shannon and Weaver, 1949), was used to classify wine types (Sparkling, Red, White, Rosé and Dessert). Table 2 presents the variables used in the ordinary least squares (OLS) model described in the next section, while Appendix presents a summary of the variable data.

*3.2 Econometric modelling*

An OLS regression approach was used to examine and estimate the factors influencing restaurant ratings by developing three econometric models (Models 1, 2 and 3), based on the variables presented in Table 2. The OLS method was selected due to the continuous nature of

**Table 1.** Michelin restaurant data description

| Region | No. of restaurants | No. of starred restaurants | 1 Star | 2 Stars | 3 Stars | € range price | €€ range price | €€€ range price | €€€€ range price |
|---|---|---|---|---|---|---|---|---|---|
| Abruzzo | 14 | 3 | 2 | 0 | 1 | 1 | 6 | 6 | 1 |
| Aosta Valley | 6 | 1 | 1 | 0 | 0 | 0 | 2 | 3 | 1 |
| Apulia | 9 | 2 | 2 | 0 | 0 | 0 | 3 | 6 | 0 |
| Basilicata | 5 | 1 | 1 | 0 | 0 | 2 | 1 | 1 | 1 |
| Calabria | 4 | 1 | 1 | 0 | 0 | 0 | 1 | 2 | 1 |
| Campania | 35 | 12 | 9 | 3 | 0 | 1 | 9 | 16 | 9 |
| Emilia-Romagna | 39 | 13 | 12 | 1 | 1 | 4 | 12 | 18 | 5 |
| Friuli-Venezia Giulia | 10 | 3 | 2 | 1 | 0 | 0 | 2 | 7 | 1 |
| Lazio | 25 | 13 | 12 | 1 | 0 | 0 | 6 | 9 | 10 |
| Liguria | 24 | 3 | 3 | 0 | 0 | 0 | 11 | 12 | 1 |
| Lombardy | 103 | 19 | 17 | 1 | 1 | 2 | 36 | 45 | 20 |
| Marche | 13 | 4 | 3 | 1 | 0 | 0 | 6 | 5 | 2 |
| Molise | 2 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| Piedmont | 82 | 20 | 17 | 3 | 1 | 5 | 41 | 25 | 11 |
| Sardinia | 6 | 1 | 1 | 0 | 0 | 0 | 3 | 2 | 1 |
| Sicily | 38 | 11 | 10 | 1 | 0 | 1 | 10 | 19 | 8 |
| Trentino-South Tyrol | 23 | 11 | 11 | 1 | 0 | 0 | 8 | 8 | 7 |
| Tuscany | 53 | 22 | 21 | 1 | 0 | 1 | 16 | 17 | 19 |
| Umbria | 6 | 1 | 1 | 0 | 0 | 0 | 3 | 3 | 0 |
| Veneto | 58 | 16 | 13 | 3 | 1 | 2 | 8 | 29 | 19 |
| Italy | 555 | 157 | 139 | 17 | 5 | 19 | 185 | 234 | 117 |

**Table 2.** Model variables description

| Variable name | Variable description |
|---|---|
| *RATING (continuous)* | *TripAdvisor's rating* − Weighted score calculated from TripAdvisor's online customer ratings, reflecting customer satisfaction based on past dining experiences |
| *REVIEW (continuous)* | *TripAdvisor number of reviews* − The natural logarithm of the total number of customer reviews on TripAdvisor, indicating customer engagement and restaurant popularity |
| *TOP10 (Dummy)* | *Inclusion in TripAdvisor's top ten* − Dummy variable indicating online visibility, with a value of 1 if the restaurant appears in TripAdvisor's Top 10 for its specific area and 0 otherwise. This serves as a proxy for the restaurant's trendiness at the time of data collection, reflecting its status among the most popular establishments |
| *MENU and MENU2 (euros)* | *Food menu price* - Average price of degustation and fixed-price gourmet menus, collected from restaurant websites, measured in euros. MENU2 is the squared value of the MENU variable, capturing non-linear effects of food menu pricing |
| *REGION (categorical)* | *Administrative region* − Categorical variable with 20 categories, each representing an Italian administrative region where the restaurant is located |
| *STAR (categorical)* | *Michelin star rating* − Categorical variable with four levels (0, 1, 2, 3) representing the number of Michelin stars awarded to the restaurant at the time of data collection, indicating quality and dining experience |
| *PRICE_RANGE (categorical)* | *Price range* − Categorical variable with four levels (€, €€, €€€, €€€€) denoting increasing price ranges, as indicated on the Michelin website, from € "on a budget" to €€€€ "spare no expense" |
| *WINE_PRICE and WINE_PRICE2 (euros)* | *Wine price* − Median value of all wines listed on each restaurant's wine list, providing a measure of central tendency that minimises the influence of outliers. WINE_PRICE2 is the squared value of WINE_PRICE, capturing potential non-linear effects of wine pricing |
| *REG_WINE (continuous)* | *Regional wines* − Natural logarithm of the number of wines from the same region as the restaurant, indicating both the size and regional focus of the wine list |
| *TYPOLOGY (continuous)* | *Wine typology diversity* − Shannon Index (Shannon and Weaver, 1949) applied to the typology of wines (Sparkling, Red, White, Rosé and Dessert) within the wine list, providing a measure of wine variety |
| *WINES (dummy)* | *Wines* – Dummy variables indicating the presence of wines in a wine list (Argentina, Australia, Austria, Chile, Croatia, France, Georgia, Germany, Greece, Hungary, Israel, Lebanon, New Zealand, Portugal, Slovenia, Spain, South Africa, Switzerland, UK and USA) |

the dependent variable. Additionally, heteroskedasticity was tested and the model was estimated with robust standard errors. Multicollinearity was assessed using both the Pearson correlation coefficient and the variance inflation factor (VIF).

Model 1 evaluates the impact of predictors on the dependent variable, *RATING*, including *REVIEW* (number of reviews), the binary variable *TOP10* (indicating presence in the TripAdvisor Top 10) and pricing variables *MENU* and its squared term *MENU2*. Additionally, this model includes the categorical variable *REGION* to account for regional effects. The specification for Model 1 is as follows:

$$RATING_i = \alpha_i + \beta_1 REVIEW_i + \beta_2 TOP10_i + \beta_3 MENU_i + \beta_4 MENU2_i + \beta_5' REGION_i + \varepsilon_i;$$

where $i$ denotes each restaurant ($i = 1, \ldots, 555.$), $\alpha$ is the intercept, $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ are the coefficients for the specified variables, $\beta_5$' represents the set of coefficients for regions included in the variable *REGION*, $\varepsilon_i$ is the error term.

Model 2 builds upon Model 1 by incorporating an interaction effect between *STAR* (Michelin star rating) and *PRICE_RANGE* (pricing category), enabling the analysis of how the combination of restaurant quality and price range influences ratings. The equation for Model 2 is as follows:

$$RATING_i = \alpha_i + \beta_1 REVIEW_i + \beta_2 TOP10_i + \beta_3 MENU_i + \beta_4 MENU2_i + \beta_5{}' REGION_i + \beta_6{}'' STAR_i \times PRICE\_RANGE_i + \varepsilon_i;$$

where $\beta_6$" represents the interaction term coefficient of *STAR* and *PRICE_RANGE*.

Model 3 further refines the analysis by including wine list characteristics. This model incorporates all variables from Model 2, along with *WINE_PRICE* and its squared term *WINE_PRICE2*, *REG_WINE* (regional wine count), *TYPOLOGY* (a diversity index for wine types), and the presence of wines from other countries on the wine list, indicated by the variable *WINES* (including countries such as Argentina, Australia, Austria, Chile, Croatia, France, Georgia, Germany, Greece, Hungary, Israel, Lebanon, New Zealand, Portugal, Slovenia, Spain, South Africa, Switzerland, UK and USA). The equation for Model 3 is as follows:

$$\begin{aligned} RATING_i = {} & \alpha_i + \beta_1 REVIEW_i + \beta_2 TOP10_i + \beta_3 MENU_i + \beta_4 MENU2_i \\ & + \beta_5{}' REGION_i + \beta_6{}'' STAR_i \times PRICE\_RANGE_i + \beta_7 WINE\_PRICE_i \\ & + \beta_8 WINE\_PRICE2_i + \beta_9 REG\_WINE_i + \beta_{10} TYPOLOGY_i + \beta_{11}' Wines_i + \varepsilon_i; \end{aligned}$$

where the coefficients $\beta_7$, $\beta_8$, $\beta_9$, $\beta_{10}$, $\beta'_{11}$, where in $\beta'_{11}$ represents the set of coefficients for each wine included in the set of dummy variables in the variable *WINES*, are associated with the wine-related variables in the model.

This sequential modelling approach allows for a comprehensive analysis of the factors influencing restaurant ratings, progressing from basic predictors to more complex variables, such as regional interactions, pricing dynamics and wine list characteristics.

## 4. Results

The results for Models 1, 2 and 3 are presented in Table 3, with all analyses performed using STATA 18 software (stata.com). To evaluate multicollinearity, both the Pearson correlation

**Table 3.** Coefficients and significance of Model 1, Model 2 and Model 3

| Dependent variable | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Rating | | | | | | |
| *REVIEW* | −0.052083 | *** | −0.053107 | *** | −0.047149 | *** |
| *TOP10* | 0.189224 | *** | 0.186963 | *** | 0.176613 | *** |
| *MENU* | 0.003577 | *** | 0.003063 | ** | 0.003775 | *** |
| *MENU2* | −0.000009 | *** | −0.000010 | ** | −0.000013 | *** |
| *REGION* | No | | No | | No | |
| STAR x PRICE_RANGE | | | | | | |
| *0#€€* | | | 0.127407 | ** | 0.124048 | * |
| *0#€€€* | | | 0.149431 | ** | 0.152551 | ** |
| *0#€€€€* | | | 0.162354 | * | 0.173212 | * |
| *1#€€* | | | 0.091161 | | 0.061306 | |
| *1#€€€* | | | 0.161110 | ** | 0.174338 | ** |
| *1#€€€€* | | | 0.184751 | ** | 0.183800 | * |
| *2#€€€€* | | | 0.231597 | ** | 0.269247 | ** |
| *3#€€€€* | | | 0.455977 | ** | 0.493372 | ** |
| *WINE_PRICE* | | | | | −0.001767 | ** |
| *WINE_PRICE2* | | | | | 0.000005 | ** |
| *REG_WINE* | | | | | −0.027026 | ** |
| *TYPOLOGY* | | | | | 0.061703 | |
| WINES | | | | | | |
| *Argentina* | | | | | 0.004607 | |
| *Australia* | | | | | −0.055687 | * |
| *Austria* | | | | | 0.021860 | |
| *Chile* | | | | | −0.024692 | |
| *Croatia* | | | | | −0.015917 | |
| *France* | | | | | 0.098385 | |
| *Georgia* | | | | | 0.052083 | |
| *Germany* | | | | | −0.013575 | |
| *Greece* | | | | | −0.005050 | |
| *Hungary* | | | | | 0.015831 | |
| *Israel* | | | | | 0.040587 | |
| *Lebanon* | | | | | 0.014980 | |
| *New Zealand* | | | | | 0.065360 | ** |
| *Portugal* | | | | | 0.038921 | |
| *Slovenia* | | | | | 0.006955 | |
| *Spain* | | | | | 0.000577 | |
| *South Africa* | | | | | −0.012061 | |
| *Switzerland* | | | | | −0.049257 | |
| *UK* | | | | | −0.035270 | |
| *USA* | | | | | 0.002996 | |
| *CONS* | 4.428968 | *** | 4.328297 | *** | 4.256735 | *** |
| Observations | 555 | | 555 | | 555 | |
| $R^2$ | 0.2525 | | 0.2639 | | 0.3069 | |
| *F*-statistic | 7.8 | | 6.05 | | 4.36 | |

**Note(s):** *$p < 0.10$; **$p < 0.05$; and ***$p < 0.01$

coefficient and VIF methods were applied across all three models, as previously mentioned. For Models 1 and 2, no multicollinearity was found, except between *MENU* and *MENU2*, which represent the same variable in linear and quadratic forms to account for nonlinear effects. In Model 3, multicollinearity was observed between *WINE_PRICE* and

*WINE_PRICE2*, as anticipated. However, this does not affect the validity of the models, since the high correlations are due to the different functional forms (linear and quadratic) of the same underlying variable, while all other variables show a VIF < 10.

Model 1 primarily examines the foundational effects of *REVIEW, TOP10, MENU, MENU2* and *REGION* on restaurant ratings. The results show that *REVIEW* has a significant negative impact on ratings, while *TOP10* has a significant positive effect. *MENU* and *MENU2* display a significant quadratic effect, with a turning point above the average, suggesting that ratings improve as *MENU* prices increase up to the turning point, after which the effect becomes negative. No significant regional effects were found in Model 1.

Model 2 extends Model 1 by incorporating additional restaurant characteristics, namely, *STAR* and *PRICE_RANGE*, providing a more nuanced analysis. The results for Model 2 are largely consistent with those of Model 1, with slight variations, such as a slightly lower turning point above the average and a reduced significance for *MENU* and *MENU2*. The interaction term between *STAR* and *PRICE_RANGE* shows a consistently positive and significant effect on ratings. However, this effect weakens for non-starred restaurants in the highest price range and becomes non-significant for Michelin-starred restaurants with lower price ranges. Regional effects remain insignificant in Model 2.

Model 3 provides the most comprehensive analysis by incorporating detailed wine list variables, including *WINE_PRICE*, *WINE_PRICE2*, *REG_WINE* and *TYPOLOGY.* This model offers an in-depth examination of how wine list composition influences restaurant ratings. The results are broadly similar to those in Models 1 and 2, with a few differences: the significance of *MENU* and *MENU2* decreases, the turning point increases to approximately €310 and the interaction between *STAR* and *PRICE_RANGE* shows reduced significance. The behaviour of *REGION* remains consistent across models. The coefficients for *WINE_PRICE* and *WINE_PRICE2* are significant but exhibit opposite signs, indicating an inverse quadratic relationship. Specifically, lower median wine prices are associated with higher ratings, while higher prices tend to lower ratings, though a positive effect emerges again at very high price points. *REG_WINE* is significant and negative, suggesting that higher ratings are inversely related to the number of regional wines on the list. *TYPOLOGY* does not show statistical significance. Finally, the *WINES* variable has no significant effect on ratings, except for New Zealand and Australia, both New World wines, where the coefficients are significant: New Zealand has a positive effect, and Australia has a negative effect on ratings.

Across all models, the restaurant characteristics variable displays consistent behaviour, with minor variations in significance. Notably, regional effects remain insignificant throughout. The intercept (CONS) is consistently significant in all models, though with a slight decline in its values, suggesting a potential baseline rating influenced by the independent variables. The R-squared values increase from 0.2525 in Model 1 to 0.3069 in Model 3, indicating that Model 3 explains the variability in ratings better than the previous models. This increase suggests enhanced explanatory power due to the inclusion of additional variables. However, despite this improvement, the R-squared values still indicate that the models do not fully capture all factors influencing the dependent variable. While *F*-statistics remain comparable across models, a slight decline is observed, from 7.8 in Model 1 to 4.36 in Model 3, likely reflecting the added complexity of Model 3.

## 5. Discussion

The results from the three models indicate that customer satisfaction is shaped by various restaurant attributes. Firstly, an increasing number of reviews is associated with lower customer satisfaction, suggesting that rising popularity through public reviews may correspond with a decline in perceived quality. This negative relationship has been previously observed in studies focused on upscale restaurants (Yoo and Suh, 2022), indicating that customer behaviour in fine dining contexts may differ from that in more casual settings.

Additionally, restaurants with high online visibility − such as those appearing on the initial search page of TripAdvisor − tend to receive higher ratings. This positive association suggests that, in the Italian fine dining context, customers are more inclined to favour restaurants that already have a strong online presence.

Findings related to food prices reveal an intriguing pattern in consumer behaviour. While higher prices tend to be associated with better ratings, this effect is not linear. A quadratic relationship indicates that beyond a certain point, very high prices negatively affect customer satisfaction. This suggests that while customers are willing to pay a premium for high-quality dining experiences, they are critical of what they perceive as overpriced offerings. These findings align with previous research showing a relationship between price and customer satisfaction (e.g. Gan *et al.*, 2016; Kim *et al.*, 2022). However, this relationship is not unbounded; in fine dining, satisfaction increases with price up to a point, after which it declines. This contrasts with studies focusing on casual dining, where lower prices are generally associated with higher satisfaction (Luca and Reshef, 2021). The opposite trend in upscale contexts may be due to elevated customer expectations − where high prices signal quality − but still, overly expensive menus are evaluated negatively.

Interestingly, all models reveal no significant territorial pattern, suggesting that geographical location does not have a measurable impact on customer satisfaction.

Notable results also emerge from the interaction between price range and Michelin recognition. All interaction terms are significant − except for the combination of low-price restaurants and one Michelin star (1#€€). The coefficients increase with price range, supporting the idea that customers expect both high quality and high prices in the upscale dining sector. Previous studies have highlighted the importance of both price and Michelin stars in shaping customer satisfaction (Rita *et al.*, 2023). In the Italian context, however, customers do not appear to value Michelin-starred restaurants that fall within a low-price range. Two key insights emerge:

(1) in the Italian upscale segment, customer satisfaction increases with price range; and

(2) satisfaction grows with the number of Michelin stars, except when combined with lower price categories.

The analysis of wine list attributes reveals several relevant implications. Specifically, lower median wine prices on the wine list are positively associated with customer satisfaction, while higher median prices are also positively evaluated − suggesting a nuanced consumer response. Customers prefer wine lists where the lower-priced options are affordable; yet also appreciate the presence of premium offerings. Given that wine prices are a central component of the dining experience (Gil Saura *et al.*, 2008), this positive response to high median prices can be attributed to the perception of enhanced product quality − since expensive wines are often seen as superior to their cheaper counterparts, confirming Schiessl's (2024) conclusions. These findings suggest that food and wine prices may influence customer satisfaction differently and should be treated as distinct elements in the evaluation of restaurant ratings.

Regarding wine list composition, the distribution of wine typologies does not significantly influence customer satisfaction. However, wine lists with a greater number of regional wines are associated with lower ratings − an intriguing result, considering that earlier studies (Čaušević and Nikolić, 2024; Perla *et al.*, 2014) have found a positive impact of domestic wines on restaurant reputation. This may reflect unique consumer preferences in the Italian fine dining scene, where guests appear to seek wines beyond the immediate regional context.

Customer satisfaction also appears unaffected by the presence of wines from specific countries of origin, except for Australia and New Zealand, which show a negative and a positive effect, respectively, though with low statistical significance. This suggests that international wine origin may play a minor role in shaping consumer perceptions compared to other wine list attributes.

Finally, this study, alongside previous research, underscores the importance of wine lists in shaping the restaurant experience. The increase in R-squared from Model 2 to Model 3 highlights that including wine list variables improves the model's ability to predict customer satisfaction, as measured by online ratings.

## 6. Conclusions, implications, limitations and future research

This study on customer ratings of Italian Michelin-starred restaurants offers valuable insights into the factors shaping consumer perceptions and satisfaction in the upscale dining segment. The findings are structured around four main themes, including customer behaviour in fine dining settings; the role of wine lists in influencing restaurant ratings; managerial implications for restaurateurs, managers and sommeliers; and strategic considerations for wine producers and wholesalers.

Customers in fine dining contexts appear to evaluate certain attributes differently compared to those in more casual dining scenarios. Higher menu prices are generally associated with greater customer satisfaction, likely reflecting elevated expectations in which price acts as a signal of quality. However, this relationship is not unlimited, as excessively high prices can negatively impact customer perceptions. Satisfaction also increases with broader price ranges and, as expected, with the number of Michelin stars awarded to a restaurant. A notable exception, however, is found in restaurants that combine Michelin recognition with low price ranges, which are not rated as positively, possibly due to perceived mismatches between expectations and value.

Wine list characteristics also play a significant role in shaping customer satisfaction. The results indicate that customers appreciate wine lists offering a balance between affordable and premium-priced wines, suggesting that price diversity is a valued feature. Furthermore, consumers tend to favour wine selections that extend beyond the restaurant's immediate regional context. This may reflect a desire for variety and discovery in the wine experience, although the specific international origin of the wines appears to be less influential than the overall structure and diversity of the list.

The study also yields relevant managerial implications for those working in upscale dining, particularly restaurateurs, managers and sommeliers. A strong online presence and a pricing strategy that aligns with perceived quality can contribute positively to restaurant performance. Importantly, the findings suggest that food and wine prices affect customer satisfaction in different ways and therefore should be considered separately in strategic planning. Restaurants receiving higher ratings tend to offer wine lists that include both affordable and premium options, highlighting the importance of price segmentation. Additionally, wine selection should avoid overemphasising regional products, instead aiming for a balanced representation of diverse origins. While international wines do not appear to play a dominant role, offering a broad spectrum without focusing too narrowly on either regional or foreign sources may improve customer perceptions. Ultimately, this study highlights the importance of restaurant distribution channels in the perspective of wine economics, especially during and after the COVID-19 period.

Beyond the restaurant setting, the findings offer strategic insights for wine producers and wholesalers. The results regarding wine price and origin provide indications of how different offerings are perceived by consumers, which can inform marketing strategies, brand positioning and partnerships with restaurants. Given the markups applied to wines in the hospitality industry, understanding how wine pricing influences customer satisfaction may support more effective business strategies in the HoReCa distribution channel.

### *6.1 Limitations and future research directions*

Despite its contributions, the study has several limitations. Firstly, the data set was constrained by the limited availability of online wine lists, resulting in the exclusion of some Italian Michelin-starred restaurants. Additionally, the study did not account for design-related features of wine lists (e.g. layout, length or number of pages), nor did it consider specific wine brands, which could potentially influence ratings.

Future research should explore cross-country comparisons to understand how cultural and regional contexts shape consumer behaviour in fine dining. Moreover, qualitative studies involving both consumers and wine experts would help identify the most influential elements of wine lists from a satisfaction perspective. Finally, further investigation into spatial dynamics and interactions among high-end restaurants could offer additional insights into competitive positioning and regional clustering effects.

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**Corresponding author**
Stefano Corsi can be contacted at: stefano.corsi@unimi.it

## Appendix

**Table A1.** Variable description

| Variable | Type of variable | Units of measure | Mean | Min. | Max. | SD |
|---|---|---|---|---|---|---|
| *RATING* | Continuous | Weighted score rating | 4.43808 | 3.10635 | 5.00000 | 0.28203 |
| *REVIEW* | Continuous | Number of online reviews | 5.76471 | 0.69315 | 8.28828 | 1.21648 |
| *MENU* | Continuous | Menu price (€) | 95.76180 | 24 | 350 | 45.03022 |
| *TOP10* | Dummy | Inclusion in TripAdvisor Top10 | 0.52612 | | | |
| REGION | Factorial | | | | | |
| *Abruzzo* | | | 0.02523 | | | |
| *Aosta Valley* | | | 0.01082 | | | |
| *Apulia* | | | 0.01622 | | | |
| *Basilicata* | | | 0.00901 | | | |
| *Calabria* | | | 0.00721 | | | |
| *Campania* | | | 0.06306 | | | |
| *Emilia-Romagna* | | | 0.07027 | | | |
| *Friuli-Venezia Giulia* | | | 0.01802 | | | |
| *Lazio* | | | 0.04505 | | | |
| *Liguria* | | | 0.04324 | | | |
| *Lombardy* | | | 0.18559 | | | |
| *Marche* | | | 0.02342 | | | |
| *Molise* | | | 0.00360 | | | |
| *Piedmont* | | | 0.14775 | | | |
| *Sardinia* | | | 0.01082 | | | |
| *Sicily* | | | 0.06847 | | | |
| *Trentino-South Tyrol* | | | 0.04144 | | | |
| *Tuscany* | | | 0.09550 | | | |
| *Umbria* | | | 0.01082 | | | |
| *Veneto* | | | 0.10451 | | | |
| STAR | Factorial | Number of Michelin stars | | | | |
| 0 | | | 0.72613 | | | |
| 1 | | | 0.23423 | | | |
| 2 | | | 0.03063 | | | |
| 3 | | | 0.00901 | | | |

(*continued*)

**Table A1.** Continued

| Variable | Type of variable | Units of measure | Mean | Min. | Max. | SD |
|---|---|---|---|---|---|---|
| PRICE_RANGE | Factorial | Level of price range | | | | |
| € | | | 0.03423 | | | |
| €€ | | | 0.33333 | | | |
| €€€ | | | 0.42162 | | | |
| €€€€ | | | 0.21081 | | | |
| *WINE_PRICE* | Continuous | Median wine price for each wine list (€) | 77.19910 | 12 | 420 | 52.42339 |
| *REG_WINE* | Continuous | Number of regional wines | 5.79540 | 2.07944 | 8.32458 | 0.98040 |
| *TYPOLOGY* | Continuous | Index of typology diversity | 1.13183 | 0.37677 | 1.51109 | 0.14706 |
| WINES | | | | | | |
| *Argentina* | Dummy | | 0.21081 | | | |
| *Australia* | Dummy | | 0.21441 | | | |
| *Austria* | Dummy | | 0.53333 | | | |
| *Chile* | Dummy | | 0.15856 | | | |
| *Croatia* | Dummy | | 0.09730 | | | |
| *France* | Dummy | | 0.97117 | | | |
| *Georgia* | Dummy | | 0.07928 | | | |
| *Germany* | Dummy | | 0.72432 | | | |
| *Greece* | Dummy | | 0.17117 | | | |
| *Hungary* | Dummy | | 0.27207 | | | |
| *Israel* | Dummy | | 0.12973 | | | |
| *Lebanon* | Dummy | | 0.20181 | | | |
| *New Zealand* | Dummy | | 0.31351 | | | |
| *Portugal* | Dummy | | 0.29190 | | | |
| *Slovenia* | Dummy | | 0.50090 | | | |
| *Spain* | Dummy | | 0.59640 | | | |
| *South Africa* | Dummy | | 0.17838 | | | |
| *Switzerland* | Dummy | | 0.07387 | | | |
| *UK* | Dummy | | 0.04324 | | | |
| *USA* | Dummy | | 0.30631 | | | |

**Note(s):** Appendix includes, for each variable used in the three models, the type of variable (continuous, dummy, factorial), a description of the variables and the unit of measure. The Table includes also the average value (Mean), the minimum value (Min), the maximum value (Max), the standard deviation (SD)