Consumer perception of price fairness and dynamic pricing: Evidence from Booking.com

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Abstract

The extensive use of online travel agencies by hotels and their guests has amplified the number of consumers who directly experiment, appraise, and evaluate how dynamic pricing is implemented by hotels. Using data retrieved from an online travel agency, we trace how room rates change according to booking day, week of stay, and room type; and we build two measures of consumer perception of price fairness based on the customer evaluation of their stay at the hotel. We find that dynamic pricing has a negative effect on price fairness: differences in the room rate among the weeks of stay and among room types are major drivers of falls in price fairness, while changes during the booking period are more tolerated by consumers.

Keywords: Room rates, Price fairness, Online booking, Dynamic Pricing
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1. Introduction

Dynamic pricing is a set of tools and procedures for managing prices and inventory to maximize revenue [98]. Developed by airlines in the 1980s, it is now utilized in other industries such as public transport, hotels, cruises, skiing industry and car rental. Until recently, in the hospitality industry, its application has been quite limited in scope [41, 78]. But, nowadays, a combination of factors, including the decline of traditional travel agencies and the rise of online ones, the availability of cheap information and communication technologies and dedicated software have induced many hotels to introduce these practices [15, 4, 1, 7].

A positive effect of dynamic pricing on revenue and profits has been found in the hospitality industry [37, 44, 91, 94, 93, 4] as well as in other economic sectors [96, 95, 69, 80]. Empirical literature in the field has also investigated the role of dynamic pricing in different ways: strategic waiting behavior [57, 117, 65], opportunistic returns [11], brand image [42], loyalty [27], and, definitively, price fairness [55, 100, 101, 19, 46, 22, 36, 47, 110, 2, 15, 106].

This paper studies the nexus between dynamic pricing and the consumer perception of price fairness in the hotel industry, by contributing to the field in several ways. First, we develop two new measures of price fairness using hotel customer evaluations retrieved from an online travel agency. Thus, we depart from current literature, which usually relies on surveys or experiments [46, 30, 29]. Second, we add to the recent literature on dynamic pricing by considering different forms of price variability coming from different pricing strategies: second-degree price discrimination; peak-load pricing; and inter-temporal price discrimination [51]. This approach is novel with respect to current literature, which only consider an overall measure of price variability [4]. Third, we refine the standard measures of dynamic pricing based on price variability by separating the "pure" variability due to a change in the pricing strategy from that due to the fact that during the selling period (cheaper) rooms are sold out. Our approach is novel also in this respect, since, differently from other papers, we both account for room availability by including the minimum available rate as well as the correct room variability. Finally, we also consider the moderating effect of the hotel category on the price fairness, an issue that has not been previously discussed in the hospitality industry.

The article proceeds as follows. In section 2, we summarise the main literature contributions about dynamic pricing practices and consumer perception of price fairness. We also define our main research hypotheses. In section 3, we describe the selected sampling design that drives the online data collection, we determine the room-rate variability for each hotel and its decomposition according to the different dynamic pricing dimensions. Moreover, we introduce variables employed in the econometric analysis presented in section 4. Some final remarks conclude the article (section 5).

2. Literature review and hypotheses

2.1. Dynamic Pricing practices

Dynamic pricing consists of a series of combined practices that aim to sell a fixed amount of perishable inventory to the most profitable mix of consumers, in order to maximize profits [see, e.g., 109]. In the hotel industry, this goal is reached by allocating "the right space, to the right consumer, at the right price, at the right time" [see, for instance, 63, 96, p. 1].

Dynamic pricing was first explored in the 1980s, after the deregulation of the US airline industry [105, 13, 14, 39, 40, 6]. It has become a widespread practice in different business sectors, mainly thanks to the development of the world wide web, e-commerce, and other online services [98, 28, 63], and, crucially, hotels [113, 51, 10, 61, 59, 86].

Hotel dynamic pricing is usually based on three main forms: peak-load pricing; second-degree price discrimination and inter-temporal price discrimination [51]. Peak-load pricing strategy occurs when hotels choose higher prices when the demand is high. Basically, hotels have always distinguished between high- and low- seasons, but recently, they tend to

Peak-load pricing and second-degree price discrimination are

on demand segmentation, i.e. consumers are separated into different categories to account for differences in their willingness-to-pay. Room rates are set according to price fences [116], which also include guest characteristics, and booking policies [62, 45]. Abrate et al. [3] identify several product differentiation criteria, such as service provision (decomposed into physical attributes, i.e. facilities and amenities), reputation (star classification and brand affiliation), and site-specific attributes (location, local attractions, climate, and beach). In addition to this, Cross [34], Lozano et al. [67] show how time of the day, day of the week, period of the year – or as a whole, seasonality – affect hotels rates. Dynamic pricing is an important component of hotel strategy: room rates are charged in order to reflect the expected demand, the current level of occupancy, and the time interval between the booking date and the date of stay.

The emergence of Online Travel Agencies (OTA) and the price transparency enabled by the Internet have allowed significant changes in how to approach hotel dynamic pricing issues, on forecasting, inventory allocations and pricing. It is, indeed, possible to evaluate the effect of price dispersion on travelers' hotel choice within OTA. In particular, Kim et al. [58] prove that travelers prefer a hotel option featuring wide price dominance dispersion. Moreover, consumer reviews, competitor rates, or benchmarking figures, all enable hotel managers to make accurate estimations of the demand price elasticity [24, 107].

The extensive use of online dynamic pricing is contributing to greatly changing the hospitality services: a consumer can now see different room rates for the same hotel which depend, for instance, on policies and booking conditions, days of stay, and the length of in-advance reservation. The dynamic pricing level of practice can, however, be different from hotel to hotel. Managers may be more or less able to forecast demand on specific dates, though some smaller facilities may lack the proper financial resources to implement and manage a full dynamic pricing system [114], even if its costs are decreasing with the evolution of information technology. Four- and five-star hotels are, indeed, the most active in terms of dynamic pricing [78].

2.2. Consumer perception of price fairness

Consumer perception of price fairness refers to the consumer's perception of whether a price is judged reasonable, acceptable, or just [110, 111]. More specifically, Xia et al. [111, p. 1] affirm that "price fairness judgments involve a comparison of a price or procedure with a pertinent standard, reference, or norm". There is a strong relationship between price fairness and consumer satisfaction [54, 8], which influences the long-term business success and affects consumer evaluation, behaviour, and willingness-to-purchase [21, 70].

A first explanation of the link between the firm price activity and the price fairness is given by the principle of dual entitlement [55]: sellers are entitled to receive a reference profit, and buyers are entitled to pay the reference price. When market conditions change, a price variation is fair if the dual entitlement is satisfied, or when its violation occurs to protect a seller's entitlement. The principle of dual entitlement is further extended in Bolton et al. [19], where price fairness concerns not only the final price but also its entire generating process (past prices, competitor prices, and costs), which influences consumer perception of price fairness and willingness-to-purchase [77]. In particular, price fairness may differ between: interdependent consumers in collectivistic cultures and in individualistic cultures [26]; short- and long-time period price changes [46]; and alignable and nonalignable costs with price increases [18].

In all these studies, price fairness involves a comparison between a price (or a procedure) and a reference. However, consumer perception of price fairness might go beyond the rational aspect, including emotional states and social behavior [22, 111].

Consumer perception of price fairness may also include the experience of other consumers: price fairness may decline when the consumer pays a price that is higher than that of others, and when the consumer observes that another consumer is paying more than her [38, 97, 110]. Knowing her own and others' prices allows the consumer to form perceptions about her own and other deals and, possibly, to become acquainted with the disutility caused by bad deals [43]. In the absence of social comparison, her own transaction value and price fairness tend to coincide [110].

The link between dynamic pricing practices and consumer perception of price fairness have been studied in many research fields [see, e.g., 64, 46]. As far as the accommodation sector is concerned, there are only a few studies. On the one hand, [30] analyze the pricing practices in the high season. They find that high room rates during high-demand periods are deemed unfair as they violate the aforementioned principle of dual entitlement. On the other hand, Viglia et al. [104] show that a hotel rate reduction in low-demand periods could decrease the consumer's reference price, making future hikes to be deemed unfair. If consumers perceive dynamic pricing practices as unfair, incremental profits generated by dynamic pricing strategies could not persist in the long term [60]. Choi and Mattila [29] study the effects of reference price on both travelers' price judgments and price fairness perceptions: hotels can use pricing structure to influence reference price and travelers' evaluation of price acceptability.

Moreover, hotel dynamic pricing affects perceptions negatively, especially when information on room-rate decisions cannot be easily retrieved or commonly accepted: unfairness of dynamic pricing practices is reduced when consumers receive justification for the prices charged [30]. Hence, a transparent dynamic pricing strategy enables consumers to understand dynamic pricing and to self-select their optimal plan [109]. Cultural and social contexts could also affect price fairness, especially in international service industries like hospitality [115, 20]. A different level of sensitivity (i.e. perception of price fairness) to hotel dynamic pricing practices is found when comparing different cultures and nationalities [31, 35], domestic and foreign brands [36], or different degrees of brand loyalty [72].

Finally, perceptions of unfairness can evolve over time [55]. Airline consumers seem to accept dynamic pricing practices better than hotel consumers do: the airline industry has practiced dynamic pricing for a longer and from an earlier time than the hotel industry. This issue is confirmed in [60], where the acceptance of dynamic pricing in the hotel industry has been proved to increase over time. Dynamic online-pricing strategies are also found to negatively affect the consumers' trust [56].

Table 1 summarizes the most relevant literature on dynamic pricing and price fairness according to our research goals in the hotel industry. This literature review table, although not exhaustive, identifies the contributions which help us in drawing the theoretical and empirical boundaries for our analysis.

Table 1: Literature review table

Article	Sector	Dynamic Pricing (DP)	Price Fairness (PF)	DP measures	PF measures	Data/experiment type	Results
[3]	Hotel	Yes	No	No	No	Fare of a single room collected from 90 to 1 day in advance, covering almost 1000 hotels in eight European capital cities	Dynamic pricing intensity depends on type of customer, star rating, and number of available rooms
[58]	Hotel	Yes	No	No	No	Three experiments involving 775 online participants, who were asked their relative preference for two hotels across two different price dispersion conditions	Travelers will prefer a hotel with wide price dispersion to a hotel with narrow price dispersion in a price comparison situation. The effect of wide (vs. narrow) price dispersion on preference for hotel is moderated by travel destination uncertainty
[78]	Hotel	Yes	No	No	No	Hotel room rates collected from Booking.com covering 62 sea-side localities collected from April to September in 2014 and 2015	Dynamic pricing is more likely applied in 4 and 5 stars hotels
[46]	Online purchase	Yes	Yes	No	7-point likert scale to measure the perception of price fairness	Two class experiments involving 421 participants, who were asked their perception of price fairness in different online purchase situations	Dynamic pricing has a negative effect on price fairness
[30]	Hotel	Yes	Yes	No	3-point likert scale to measure the perception of price fairness, then binarized	240 interviews of US travellers on hotel dynamic pricing	Hotel room rate dynamic pricing does not reduce the customer perceptions of fairness, especially when prior information is available
[29]	Hotel	No	Yes	No	7-point likert scale to measure the perception of price fairness	192 hotel guests questionnaires based on hypothetical hotel-booking situations	Price fairness is affected by internal and external reference prices
[104]	Hotel	Yes	Yes	No	No	Two experiments including 60 undergraduate students (study 1) and 140 hotel customers (study 2). Participants were asked on their reference price formation	To form their reference price, customers mainly consider their past lower prices. Price fairness is affected by the pricing strategy of competitors

2.3. Hypotheses

Previous discussion emphasizes that price fairness is particularly important in the hotel industry since a variety of pricing practices have increasingly raised fairness issues [89].

In particular, from our analysis of the literature contributions on the perception of price fairness (subsection 2.2), it emerges that dynamic pricing practices and structure is likely to have a negative impact on price fairness. Indeed, given the principle of dual entitlement, when a consumer observes a change in price that is not justified by cost variations, its perception of price fairness reduces [55]. Since hotels using price discrimination practices charge (and modify) room rates in such a way that are not justified by cost variations, consumers will consider such a practice as unfair [19, 77, 18]. Based upon this reasoning, we develop the following first hypothesis:

> *H1. The larger the rate variability, the lower the consumer perception of price fairness.*

Moreover, hotel can price discriminate using different approaches [see, e.g., 51]. They can apply different prices for different room types (second-degree price discrimination), for different periods of stay (peak-load pricing), and for different periods of booking (inter-temporal price discrimination). Each of these aspects can affect negatively the consumer perception of price fairness [30, 56, 38, 97, 110]. Based upon this reasoning, we develop the following set of hypotheses:

> *H2.1. The larger the rate variability due to the different room types, the lower the consumer perception of price fairness*;

> *H2.2. The larger the rate variability due to a variation in the periods of stay, the lower the consumer perception of price fairness*;

> *H2.3. The larger the rate variability due to a variation in the different periods of booking, the lower the consumer perception of price fairness.*

From previous discussion, we know that unfairness of dynamic pricing practices is reduced when consumers receive justification for the prices charged [30]. Since in four- and five-star hotels, differently from three-star hotels, the owner usually delegates to frontline employees (senior managers, junior managers, and supervisors) for dealing with customers [53], the possibility to receive sound justifications for price changes reduces. Therefore, we expect that there exists a moderating effect of three-star hotels on price fairness. Based upon this reasoning, we develop the following set of hypotheses:

> *H3.1. The three-star hotels positively moderate the relationship between the price fairness and the total rate variability, ie. being a three-star hotel will reduce the negative impact of RV on price fairness compared to four- and five-star hotels.*

H3.2. The three-star hotels positively moderate the relationship between price fairness and the rate variability due to different room types, ie. three-star hotels have a lower negative impact of RVr on price fairness than four- and five-star hotels.

H3.3. The three-star hotels positively moderate the relationship between price fairness and the rate variation due to a variation in the period of stay, ie. three-star hotels have a lower negative impact of RVw on price fairness than four- and five-star hotels.

H3.4. The three-star hotels positively moderate the relationship between price fairness and the rate variability due to a variation in the different periods of booking, ie. three-star hotels have a lower negative impact of RV on price fairness than four- and five-star hotels.

From previous discussion, price fairness is both affected by prices higher or lower than the reference price, however a large use of online dynamic pricing techniques in the hotel industry has caused a reduction of the reference price [104]. Therefore, it is very likely that consumers will consider the price paid on the web larger than their reference price [48]. This leads to the last hypothesis:

H4. The higher the room rate, the lower the consumer perception of price fairness.

3. Data and variables

3.1. Data collection

The proposed analysis is based on public online information about Italian hotels. In Italy, indeed, are concentrated some of the most popular tourist attractions in the world. Moreover, its tourism sector is not only a crucial economic lever, but it is also widespread both in urban and rural territories, thus involving different types of tourism destinations.

Our own dedicated web crawling system, written in Python, has been developed to collect suitable data from Booking.com, one of the most popular hotel booking online platforms [2]. The web crawler connects to the web pages of the sampled hotels, according to a predefined seven-day length of stay, and stores extracted information in a dedicated database. It collects two levels of information. At the hotel level, it traces the hotel address and name, its number of stars, overall and attribute-specific consumer satisfaction scores (relating to cleaning, staff, comfort, service, location, wi-fi and value-for-money). At the room level, the web crawler stores the room rate for the stay, room features (bed type, room size in square meters, presence of a balcony or terrace, TV and free wi-fi, air conditioning, private pool, bath or spa) and policy options (the inclusion of breakfast, free cancellation, and compulsory prepayment).

In practice, the database comprises 1,100 Italian hotels for a seven-day booking period (always from Saturday to Saturday), ranging from the first week of July 2018 to the last week of October 2018. Hotels were randomly sampled from those located in 22 Italian touristic cities, selected from the ISTAT [49, p.10] list which ranks the top-50 Italian municipalities based on the presence of tourist facilities. In addition, we add Aosta (for mountain municipalities) and Perugia (for cultural/artistic heritage cities) in order to provide a more satisfactory representation in terms of geographical location (North, Center, South and Islands) and destination type (mountain, seaside and cultural/artistic heritage cities) (see tables A.1 and A.2). The limited number of selected cities is functional to the use of fixed-effect methods, which are usually preferred to control for local specificities when different tourism destinations are highly heterogeneous.

Therefore, the following sampling design was used for data collection: for each of the 24 selected cities, all the available hotels on Booking.com website were collected and 10 five-star, 15 four-star, and 25 three-star hotels were randomly sampled. This stratification strategy rests on the idea of measuring the three-stars moderating effect ensured by the balanced split between three-star vs four- and five-star hotels. In 2018, more than the 55% of the Italian hotels enjoy the three-star classification, while the four and five-stars are the 19,7% of the total [50]. This is principally due to the fact that the Italian hotel system is highly fragmented, family-run, concentrated on intermediate quality structures (mainly three stars), which very rarely belong to a hotel chain. When the number of hotels in a given star category was not sufficient to reach the desired sample dimension, the required number of hotels were randomly selected from a lower star category. Following Tso and Law [99], three-and-a-half and four-and-a-half star hotels were treated as three- and four-star hotels, respectively (see table A.2).

The selected number of hotels ensures a homogeneous representation of each city, as well as adequate numbers in different hotel categories. We decided not to take into account hotels with less than three stars given that, in general, their managers rarely apply dynamic pricing techniques [see, e.g., 78]. At the end of the data collection process, which started on 1 May 2018 and ended on 10 August 2018, we had 378,961 room rates and 995 rating scores. In figure 1, we represent different steps and stages of the data collection process. A crawler is active on our cluster, and it is able to connect to the Booking.com website on a daily basis, as depicted in the top temporal line.

Crawler activity started in May 2018 and ended in August 2018. In this period, for each day, the crawler connected to the Booking.com website and searched for room rates, reviews, as well as room and hotel features, simulating a customer on a hotel booking online platform. On a particular search day, data was collected in the forthcoming weeks, each week at a time, from this day up to the last week of the summer holiday period (31st October 2018). The starting week for the check-in date is instead 1st July 2018. The data record consists of room rates, room features, hotel global and value-for-money reviews and score for said week w, booking day d and a room type r; the data record is then saved and stored on our cluster. The variable "booking day" was constructed as the difference between the date of check-in and the current date of search day. The crawler has been active for May 2018 up to August 2018, while room rates have been collected for the whole summer holiday period (from 1st July to 31st October 2018).

The final database consists of a total of 378,961 price observations for 995 hotels, 18 check-in dates and a varying number of booking days. The number of booking day is, in fact, not a constant due to our data collection strategy, as it varies according to the search day, while the ending date for check-in is kept fixed (31st October 2018).

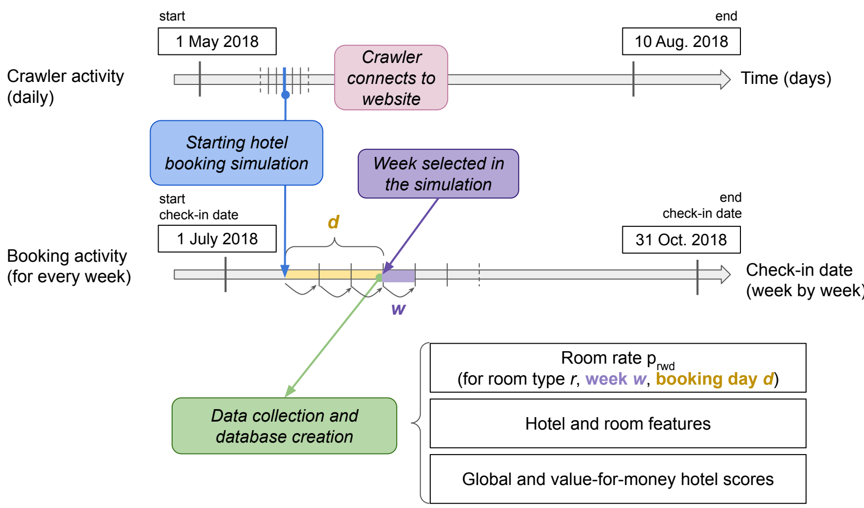

Figure 1: Data collection process

Global and value-for-money hotel scores, which appear on the Booking.com hotel main page, were also collected. These two ratings are computed by Booking.com for each hotel and are based on the scores left by single guests after their stay in the past year. Each guest was asked to give scores for a set of items such as value-for-money, services, wi-fi, etc. In particular, the global score is determined as the average of the specific item scores. Reviews and hotel rating in our database range from 30-08-2016 to 30-08-2018; global and value-for-money scores are collected from the website at the end of the sampling period. Without loss of generality, due to the observed limited variability over the sample period, these ratings were collected at the end of the web crawling process and related to the past year's scores. The validity of this collection approach is confirmed by [16], which prove the similarities across many online platforms of hotel ratings and their evaluation pattern stability over time. These two variables are used to develop two measures of consumer perception of price fairness, presented in the next subsection.

3.2. Measuring consumer perception of price fairness

A major issue in our analysis is to provide empirical measures of price fairness which here rest on the use of customer satisfaction scores.

At the end of the stay, guests reserving on Booking.com are asked their judgement on different dimensions of their experience, including cleaning, staff, comfort, service, location, wi-fi and value-for-money; a global valuation measure is then computed as the arithmetic mean of previous indicators. Recently, Booking.com has announced the introduction of changes to its rating system, including the fact that guests will directly compile the "overall" score [79]. However, guests are not directly asked their judgement about their perception of price fairness [81]. Fairness, value-for-money and global value have been shown to be related but conceptually distinct constructs, and, therefore, they cannot be used interchangeably [85, 9]. We show, however, that a fairness measure can be obtained from the combination, and possibly a transformation, of two customer satisfaction scores. To this aim, we now consider a first measure based on the difference between value-for-money score and global score.

On the one hand, the value-for-money score ($vfms$) is a monetary measure of satisfaction [81]. According to the equity theory, value-for-money score increases if the sacrifice (price paid) lowers and the benefit (accommodation in the hotel room) raises [5]. Thus, concerning our analysis, value-for-money score reflects the discrepancy between the room value (rv) and the price paid (pp) by hotel guests.

On the other hand, the global score (gs) is an overall evaluation concerning guest satisfaction about the room attributes and includes monetary and non-monetary judgements [81]. According to the discrepancy theory, customer satisfaction is a process and corresponds to an evaluation between a consumer's expected level of product performance and the consumer's observation of actual performance after product usage [84, 88]. Thus, the global score increases if the product performance increases. With regard to our analysis, the global score can be interpreted as the discrepancy between the average value of different attributes of the room and the expected value of these attributes, or more succinctly, the discrepancy between room value (rv) and the expected room value (erv). Thus, our first proposal is:

$$\begin{aligned} \mathrm{M}_1 &= vfms - gs \\ &= (rv - pp) - (rv - erv) \\ &= erv - pp. \end{aligned} \tag{1}$$

From Eq. (1), we find that the difference between the two scores, M_1, is simply the difference between the expected value and the price paid. This measure can be further interpreted by noting that the expected room value may correspond to the expected price of the room, i.e. to the reference price (rp), especially when social comparison is limited [110, 30]:

$$\mathrm{M}_1 = rp - pp. \tag{2}$$

Thus, Eq. (2) indicates that M_1 is a measure of the transaction value, which captures the discrepancy between the expected price and the price paid. This measure can also be interpreted as price fairness since the value-for-money score is usually lower than the global score [82], meaning that since the reference price tends to be lower than the price paid, a reduction in the price paid increases both the transaction value and the price fairness.

We also consider a second measure of consumer perception of price fairness:

$$M_2 = -|M_1| = -|rp - pp|. \tag{3}$$

In this case, M_2 equals zero when the reference price coincides to the price paid and is positive and increasing when rp and pp diverge. Thus, M_1 is always decreasing in the price paid while M_2 is first decreasing and then increasing in the price paid.

3.3. Room-rate variability and its decomposition

Data collected from the Web are at different levels of aggregation. In order to conduct the econometric analysis, we converted all the available information to a hotel-level scale. Three main methodological issues arise when we transform room-rate data. First, we need to manage the problem of missing room rate values. Second, we need to construct a measure of dynamic pricing intensity. Finally, we need to decompose the latter in a useful way to account for the different dynamic pricing sources of rate variability.

During the booking period, d days before the check-in, all hotel rooms of type r for a given week-of-stay w can be sold or taken off the OTA platform. Therefore, it is no longer possible to retrieve information on the room rate, p_{rwd}, while, for the same room type r but for a different week-of-stay $w' \neq w$ and / or booking day $d' \neq d$, one or more rooms and the corresponding rate, $p_{rw'd'}$ might be retrieved. The booking day variable counts the number of days in advance of the simulating booking process from the check-in date, and it is crucial in the investigation of dynamic pricing strategies [2]. Note that coping with the absence of room rate values could be read as a further dynamic pricing strategy, to be suitably investigated. Missing room rates may appear for one of the following reasons: only some room types are online to signal the hotel's existence; all rooms are online and for occupancy reasons a missing rate appears; rooms are sold online only at the last minute; only a few rooms are sold online; etc.

Since in our sample 169,973 observations are not available (about 30.8% of the sample), our database has a relevant missing value problem [see e.g. 71]. The unavailability of room rates in the collected data is also related to the other two methodological concerns, i.e. the construction of global and disaggregated measures of dynamic pricing intensity, which are based on hotel room-rate variability. If some rates are missing, such measures can be biased. For example, consider a hotel with two room types – standard and superior – which have different rates. Our selected measure of the room-rate variability is the sample room-rate variance based on the rates retrieved from the OTA platform (a detailed explanation will follow later). For the same set of rates, the room-rate variability will be low if posted rates, given missing values, are mainly of one of the two room types, while it might be higher if both room types were more equally represented. Moreover, taking into consideration the week-of-stay and the booking day, the unavailability of some room rates results in a rate variability that does not reflect the real dynamic pricing activity. For example, if during the booking period we observe alternatively either standard room rates or superior ones, using a measure that does not account for missing values, we could wrongly assume that there is variability in the booking day dimension, while this might not be the case.

In order to address this methodological issue, we propose a method to preprocess data and to estimate the missing rates that cause the underlying variability. This regression-based approach is applied to each hotel separately: the dependent variable is the natural logarithm of the single room rate, while the independent variables are room-type fixed effects which allow the average rate difference between room types to be measured. The missing log-rate is then replaced with an estimated value, g_{rwd}, which accounts for both the rates of the same week of stay and those for the booking day of a reference room whose rate is observed; and for the average rate difference between a particular room and the reference room (see Appendix B for technical details).

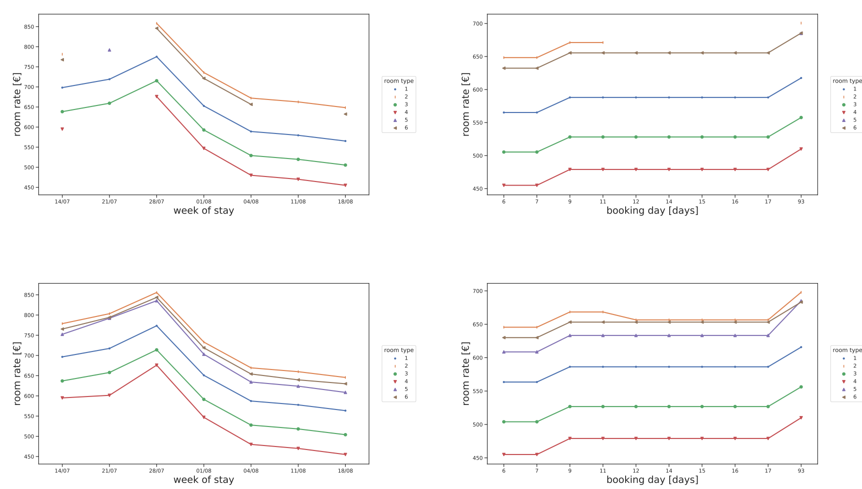

Figure 2: Observed and imputed hotel rates (in Euro) for a selected hotel are reported in the top and bottom panels. The left and right panels refer, respectively, to rate changes over different weeks of stay and booking day. The latter counts the number of days in advance of the simulating booking process from the check-in date.

Figure 2 provides an example of how the imputation procedure works, while in table 2 we illustrate the main summary statistics for observed and estimated rates. Interestingly, figure 2 offers some anecdotal evidence that hotels use a baseline room rate and multiplicative factors to set the rates for all room types. In general, the use of multiplicative coefficients avoids unjustifiable peaks or rate trends, as well as unrealistic negative imputed values. In order to test the efficacy of the imputation procedure, we have randomly removed 5% of observations from the sample, and then applied the same procedure. The coefficient of variation computed using the difference between predicted and observed log rates of the random sample is 0.79%, which confirms the accuracy of the proposed imputation procedure.

Table 2: Summary statistics of observed and estimated room rates

	count	mean	std	min	25%	median	75%	max
Observed	378,961	1,744.82	3,355.61	140.00	693.00	1,036.00	1,666.00	119,735.00
Estimated	168,728	1,915.76	3,450.71	169.23	775.34	1,186.27	1,878.01	137,232.64
Total	547,689	1,792.63	3,383.09	140.00	713.00	1,074.10	1,729.33	137,232.64

Dynamic pricing activity consists of using a variety of room rates for different room types, weeks of stay, and booking days [98]. The intensity of the dynamic pricing activity can be determined by studying the variation in its room rate. Our measure of room-rate variability (RV), and, therefore, of dynamic pricing activity, is the sample variance of hotel log-room-rates over the room type r, the week of stay w, and the booking day d. The rate variability is computed as follows:

$$RV = \frac{1}{n-1} \sum_{r=1}^{R} \sum_{w=1}^{W} \sum_{d=1}^{D} \left[g_{rwd} - \overline{g}\right]^2 , \tag{4}$$

where $n = R \times W \times D$ is the total number of rates observed for each hotel, and $\overline{g}$ is the average log-rate.

In what follows, we investigate different dimensions of the dynamic pricing activity, taking advantage of a suitable RV decomposition. More specifically, we consider three dimensions which characterize the room-rate variability – the room type r (RVr), the week of stay w (RVw), and the booking day d (RVd) – which are, respectively, intended to capture three well-established price discrimination strategies [see, e.g., 51]: second-degree price discrimination; peak-load pricing; and inter-temporal price discrimination.

To this aim, we perform a three-way fixed effect ANOVA [see, e.g., 25, 33] over the log-room-rates, in order to quantify the role of these three strategies. We assumed set-to-zero linear constraints to deal with the exact multicollinearity of the three-way ANOVA. The model is run without the interaction parameters of explanatory variables [see 102, and the references therein]. This guarantees that the different room type effects can be easily distinguished, avoiding over-representation and parameter identification issues. To prevent the latter and due to a low booking day rate variability, d is forced to have fixed-length classes of three days. See Appendix C for further details.

To the best of our knowledge, this is one of the first time that a three-way ANOVA has been used, not to identify the effects of different (categorical) covariates, but rather to capture the induced variability decomposition. Following this approach, the total hotel rate variability is decomposed according to the three hotel-specific dynamic pricing effects, given the analysis of the variance table of the three-way ANOVA.

The total sum of square (SST) of hotel room rates is $SST = (n-1)\,RV$, where n indicates the total number of hotel rates. First, SST is equal to the sum of two components: the regression sum of squares (SSR), which represents the rate variability induced by dynamic pricing dimensions; and the error sum of squares, which expresses the portion of rate variability not explained by the dynamic pricing components. Second, the analysis of the variance table allows the regression sum of squares among the selected covariates to be split, i.e. $SSR = SSr + SSw + SSd$, where the three components refer to the room type, the week of stay, and the booking day, respectively.

Hence, the three-way ANOVA, performed on each sampled hotel, allows to decompose the dynamic pricing effects on the log-room-rate according to the specified dimensions as shown in Table B.1. The different estimated effects (sum of squares divided by the number of degrees of freedom) of r, w and d in the ANOVA for each hotel represent the decomposition of the total variability in RVr, RVw and RVd, respectively.

Some descriptive statistics based on the three-way ANOVA are shown in table 3. The adjusted R^2 and the p-value confirm, respectively, a high goodness-of-fit and an overall significance of the estimates. The former is confirmed by an adjusted R^2 higher than 0.97 in 75% of the sampled hotels. However, to develop our analysis, 105 hotels have been excluded from the study due to their highly incomplete price time series, which could not efficiently be imputed and do not allow the three-way ANOVA to be performed.

Table 3: Summary statistics of the R^2_{adj} and the p-value for the F test, obtained from the 995 performed three-way ANOVA

	count	mean	std	min	25%	median	75%	max
R^2_{adj}	995	0.975	0.035	0.556	0.970	0.985	0.994	1.000
p-value of the F test	995	0.000	0.000	0.000	0.000	0.000	0.000	0.000

3.4. Variables

In order to study the impact of dynamic pricing on consumer perception of price fairness, we now present the variables employed in the empirical analysis.

Dependent variable. We use the two different measures of consumer perception of price fairness ($CPPF$) at hotel level described in section 3.2, Eq. (1)

- (3):

$$\begin{aligned} \mathrm{CPPF}_1 &= \mathrm{M}_1 = \quad \text{value-for-money score} - \text{global score}, \\ \mathrm{CPPF}_2 &= \mathrm{M}_2 = -|\text{value-for-money score} - \text{global score}|. \end{aligned}$$

The first measure, CPPF_1, is based on the definition of transaction value which corresponds to price fairness when the value-for-money score is less than the global score, meaning that the price paid is higher than the reference price and, therefore, a reduction in the price paid increases both the transaction value and the price fairness. This emerges in about 90% of the cases, consistently with other studies [82]. Using the second measure (CPPF_2), we are assuming that not only an exceed of the price paid with respect to the reference price could induce an unfairness perception, but also an excessively low price paid could results, even if in an economic advantage for the consumer, also in an less fair perception [110]. Namely, the first measure identifies forms of price fairness when the price paid is equal or lower than the reference price, while the second measure accounts that there can be fairness issues when the price paid diverges (or too high or too low) from the reference price.

Independent variables. The other hotel variables considered in the econometric analysis can be grouped into three categories: dynamic pricing strategies; hotel characteristics; and guest characteristics.

Dynamic pricing strategies are assumed to affect both the room rate and the reference price. The average minimum observed hotel log rate (*Room rate* variable) is the average, over weeks and booking periods, of the observed minimum rate. This variable is intended to represent rates paid by consumers, or, at least, by the more price-sensitive ones. In order to account for the paid rates, the *Room rate* variable has been based only on the observed rates. The other two variables are: *Breakfast rate* and *Free cancellation*. The former considers the required extra rate for breakfast, computed as the average additional breakfast rate over hotel room types. The latter is the percentage of room rates which include a free cancellation option.

Based on the three-way ANOVA previously presented, we consider hotel-specific variables which measure the rate variability and its decomposition. In particular, we take into account the *Total rate variability* (RV), and its decomposition according to the room (RVr), the week of stay (RVw) and the booking day (RVd).

The variables for the hotel characteristics are as follows. A dummy variable – labeled *Three stars* – which identifies three-star hotels with respect to four- and five-star hotels, is justified by the dissimilarities between the rates and facilities offered by these two groups of hotels. We specify whether the hotel location is in a mountain destination – using the dummy variable *Mountain*– instead of at the seaside or in cultural/artistic heritage cities (which represent the reference category). We also consider the number and the average size (in square meters) of room types, labeled *Room diversity* and *Room size*, respectively. The former variable is employed as a proxy for the hotel dimension, information not available on Booking.com at the time of data collection. A dummy reflecting the presence of the *Parking* complete this group of variables.

Finally, three variables related to guest characteristics are constructed. First, variable – labeled *Foreign* – aims at identifying those hotels having a share of foreign speaking visitors over the total above the median. To do this, for each hotel, we have computed the ratio between reviews offered in a foreign language (French, English or German) and those in Italian. Then, we have used this variable to create a dummy variable equals one when the first variable is above the median value. We have limited our analysis to Italian and the three main popular foreign languages spoken by tourists staying Italy to reduce the data collection burden as comments for each language and for each hotel must be retrieved separately. In total, we archived 155,455 reviews; 72,398 in Italian, 23,096 in French; 24,667 in German; and 35,294 in English.

Second, a variable – labeled *Male* – represents the percentage of male reviewers over the total number of reviewers, collected as discussed above. Note that the gender is not a directly available information. To construct this variable, we took advantage of the Python library gender-guesser by matching the reviewer's name and nationality with an international dictionary of first names and genders.

Third, the number of collected reviews (as illustrated above) of the hotels at the end of the web crawling process divided by the total number of hotel room types comprises the variable labeled *Review*.

Summary statistics of the presented variables are shown in table 4 while table 5 shows the correlation matrix.

Table 4: Main summary statistics of the price fairness (CPPF.), the total rate variability (RV) and its components (RVr, RVw and RVd), the *Room rate*, together with *Room diversity*, *Room size*, *Breakfast rate*, *Free cancellation*, and *Review*

	mean	std	min	max
Price Fairness				
1.a CPPF_1	-0.394	0.346	-1.650	0.800
1.b CPPF_2	-0.434	0.295	-1.650	0.000
Dynamic Pricing				
2. Total rate variability (RV)	0.108	0.079	0.000	0.479
3. Room (RVr)	0.071	0.061	0.000	0.430
4. Week of stay (RVw)	0.032	0.045	0.000	0.324
5. Booking day (RVd)	0.002	0.004	0.000	0.082
6. Room rate	6.723	0.561	5.223	9.031
7. Breakfast rate	1.132	3.450	0.000	40.456
8. Free cancellation	0.570	0.300	0.000	1.000
Hotel characteristics				
9. Room diversity	5.1555	2.541	1.000	23.000
10. Room size	23.286	14.765	8.050	390.441
Guest characteristics				
11. Review	34.440	32.058	0.167	267.000
12. Male	0.252	0.435	0.000	1.000
13. Foreign	0.501	0.500	0.000	1.000

N=995

Table 5: Correlations of variables in table 4

	1.a	1.b	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
Price Fairness														
1.a $CPPF_1$	1,00													
1.b $CPPF_2$	0,91	1,00												
Dynamic Pricing														
2. Total rate variability (RV)	-0,12	-0,12	1,00											
3. Room (RVr)	-0,09	-0,10	0,78	1,00										
4. Week of stay (RVw)	-0,07	-0,07	0,60	-0,01	1,00									
5. Booking day (RVd)	-0,04	-0,03	0,26	0,02	0,27	1,00								
6. Room rate	-0,75	-0,71	0,09	0,09	0,03	0,02	1,00							
7. Breakfast rate	-0,17	-0,18	0,00	0,00	-0,01	0,00	0,24	1,00						
8. Free cancellation	0,07	0,06	-0,02	-0,06	0,04	0,03	-0,10	0,05	1,00					
Hotel characteristics														
9. Room diversity	-0,24	-0,22	0,04	0,03	0,02	0,07	0,23	0,10	0,08	1,00				
10. Room size	-0,34	-0,34	0,07	0,08	0,00	-0,03	0,49	0,21	-0,08	0,31	1,00			
Guest characteristics														
11. Review	0,18	0,19	-0,04	0,00	-0,06	-0,03	-0,15	0,03	0,13	-0,36	-0,17	1,00		
12. Male	-0,03	-0,01	0,02	0,01	0,03	0,00	0,08	0,09	-0,13	0,02	0,17	-0,15	1,00	
13. Foreign	-0,11	-0,10	-0,02	-0,03	0,00	0,04	0,23	0,19	-0,01	0,12	0,09	0,25	0,00	1,00

N=995

4. Econometric analysis

Our analysis is based on the following model:

$$\text{CPPF}. = \alpha + \boldsymbol{\beta}\, DP\, variables + \boldsymbol{\gamma}\, controls, \tag{5}$$

where α identifies the global intercept; $\boldsymbol{\beta}$ is the vector of coefficients for dynamic pricing variables; and $\boldsymbol{\gamma}$ is the vector of coefficients for control variables such as hotel and guest characteristics. To overcome heteroskedasticity issues, we take advantage of White's robust standard errors leading to heteroskedasticity-consistent estimator [108]. We consider two different dependent variables as well as two different estimation methods. In the first case, we employ an OLS model with robust standard errors using CPPF_1 as dependent variable, while in the second one, we employ a Tobit estimator since CPPF_2 is a right truncated variable.

The main results concerning the modelisation of CPPF_1 are shown in tables 6 and 7 while the study of the determinants of CPPF_2 are reported in tables 8 and 9. In general, tables 6 and 8 indicate how total rate variability affects price fairness, while tables 7 and 9 analyze the impact of the three components of the room-rate variability, i.e. room, week of stay, and booking day, respectively. In columns (2) and (4) of each table, we investigate the moderating role of three-star hotels on the rate variability.Moreover, in columns (3) and (4), we re-estimate previous model by using a city-fixed effect.

Dynamic Pricing variables. In general, the negative and highly significant coefficient of the *Room rate* variable shows that the outcome of the dynamic pricing strategy – the available room rates – is the major determinant of CPPF_1 and CPPF_2. Indeed, when hotel pricing strategy includes multiple room rates, the minimum room rate paid by consumers is more likely to be affected by the availability of cheap rooms than by the room rate variation over the booking period. Thus, if room rate levels are set in such a way that cheap rooms are sold much faster than the other rooms, the minimum rate level can rise significantly even if the cheapest rate levels are low. Consequently, dynamic pricing activity, by affecting the available room rates and, especially, the minimum ones (i.e. those offered to the most price-sensitive consumers), has a strong impact on consumer evaluations. This finding confirms that the higher room rates are expected to be less fair (*H4*), since the higher the rates, the farther consumers are expected to be from their reference price.

A second set of variables does not consider the dynamic pricing strategy effects on room availability but focuses on hotel dynamic pricing activity, i.e. the room-rate variation, which the dynamic pricing strategy of the hotel can generate. As already noted, an intensive dynamic pricing activity yields large price differentials, which may reduce the reference price [104]: buyers tend to associate the reference price with lower prices usually charged in the period of low demand. Since our measure of price fairness should reflect the price paid by guests with respect to the reference price, a drop in the latter should negatively affect price fairness.

We find that the *Total rate variability* variable (RV) has a negative and significant impact on CPPF$_1$ and CPPF$_2$ which confirms *H1* (see tables 6 and 8). Namely, an increase in RV induces a reduction of the two price fairness measures. These results remain still valid also accounting for the moderating role of three-star hotels and using a city-fixed effect control. In this regard, we notice that the interaction between RV and three-stars results in positive and statistically significant effects except only for the second model of table 6.

As far as RV decomposition is concerned in table 7 and 9, the negative coefficients for RVr and RVw, even if not always significant, suggest that the dynamic pricing activity may be responsible for a loss of price fairness along different dimensions. In particular, the coefficient of the *Room rate variability* variable (RVr) has a negative and statistically significant impact on consumer perception of price fairness, except in column (2) of table 7. This empirical evidence is weaker when considering CPPF$_1$. The coefficient of the *Week of stay rate variability* variable (RVw) has the greater magnitude and has always a negative and statistically significant sign in all models. Differently, the *Booking day rate variability* variable (RVd) does not play any significant role in any estimated model.

The moderating role of three-star hotels in describing the effect of RVr on CPPF$_2$ suggests a reduction of the price fairness in four- and five-star hotels in response to increments in the room rate variability: four- and five-star hotels show a RVr slope equal to -0.354 and -0.316; and three-star hotels shows a RVr positive (but not statistically significant) slope of 0.021 and 0.111 for models in columns (2) and (4) of table 9, respectively. Considering both *Week of stay rate variability* and *Booking day rate variability* variables, the moderating role of three-star hotels on them has no statistical evidence.

Thus, *H2.1* and *H2.2* have been confirmed by our study, while there is no empirical evidence in favour of *H2.3*. Moreover, our econometrics analyses confirm *H3.1*, and partially support *H3.2* (only for CPPF$_2$). Differently, there is no statistical evidence in favor of *H3.3* and *H3.4*.

The last two dynamic pricing strategy variables included in the analysis are *Breakfast rate* and *Free cancellation*. *Breakfast rate* has a negative impact on both CPPF$_1$ and CPPF$_2$, even if in some models their coefficients are not statistically significant. The negative sign of the *Breakfast rate* variable, as largely expected, provides additional evidence that price fairness is negatively affected by payment requests, especially when consumers interpret them as the application of price discrimination techniques. In general, in the hospitality sector, these ancillary services induce a reduction in the perceived price fairness [83, 32].

Differently, the *Free cancellation* variable never shows a statistically significant effect.

Hotel characteristics variables. Tables 6-9 show that the *Three stars* variable has always a positive and statistically significant sign, consistent with [78] and [99], i.e. highly-rated hotels are perceived to be less fair.

Hotels located in mountain destinations are associated with a lower level of price fairness when compared with *Seaside* or *Cultural/artistic heritage* cities. This could also be explained by the different shares of business travelers according to different types of destinations. Thus, when evaluating hotel price fairness with both measures, different reference prices are employed by consumers which induce a different price fairness perception, all things being equal [see, e.g., 75].

The *Room diversity* variable only marginally reduces CPPF_1 in all models while CPPF_2 is not affected by the number of different room types.

By contrast, the *Room size* variable increases the consumer perception of price fairness considering both CPPF_1 and CPPF_2 measures.

The remaining hotel control (*Parking*) has a not statistically significant effect on price fairness.

Guest characteristics variables. All guest characteristics included in the analysis have a positive and statistically significant impact on price fairness for both CPPF_1 and CPPF_2. The unique exception concerns foreign guests percentage in models in columns (3) and (4) of tables 8 and 9 which shows a not statistically significant point estimate. On average, male and foreign guests assign higher price fairness levels. This finding is consistent with [12], where males' evaluations result in higher price fairness than those of females, and with [90], where there is evidence that many foreign tourists visit cultural/artistic heritage cities and have very positive evaluations. The positive effect of the *Foreign* variable can also be due to a cross-cultural effect [see, e.g., 31], and/or to differentiated hotel strategies to better satisfy the preferences of consumers with different nationalities [92]. Moreover, a greater number of reviews increases both CPPF_1 and CPPF_2, even if only marginally, meaning that reviews help consumers to identify the strengths and weaknesses of the facility and to better select the one which is more suitable for them [103].

Table 6: Estimates of the price fairness ($CPPF_1$) determinants (OLS model with robust standard errors)

	Dependent variable: $CPPF_1$			
	(1)	(2)	(3)	(4)
Dynamic Pricing				
Room rate	-0.438***	-0.437***	-0.426***	-0.424***
	(0.018)	(0.018)	(0.019)	(0.019)
Total Rate var.	-0.214**	-0.295***	-0.155*	-0.265**
	(0.086)	(0.112)	(0.082)	(0.104)
Total Rate var. * three stars		0.180		0.244+
		(0.171)		(0.163)
Breakfast	-0.033	-0.035	-0.049*	-0.052*
	(0.030)	(0.030)	(0.030)	(0.030)
Free cancellation	-0.017	-0.016	0.002	0.004
	(0.028)	(0.028)	(0.027)	(0.027)
Hotel Characteristics				
Three star	0.088***	0.070***	0.101***	0.076***
	(0.017)	(0.025)	(0.017)	(0.024)
Mountain	-0.100***	-0.101***	-0.091**	-0.091**
	(0.023)	(0.023)	(0.039)	(0.039)
Room diversity	-0.007**	-0.007**	-0.007**	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
Room size	0.096***	0.097***	0.113***	0.114***
	(0.032)	(0.032)	(0.028)	(0.028)
Parking	-0.014	-0.014	-0.044***	-0.044***
	(0.015)	(0.015)	(0.016)	(0.016)
Guest Characteristics				
Review	0.001**	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.050***	0.051***	0.051***	0.051***
	(0.018)	(0.018)	(0.018)	(0.018)
Foreign	0.041**	0.041**	0.037**	0.037**
	(0.016)	(0.016)	(0.016)	(0.016)
Constant	2.250***	2.247***	2.038***	2.033***
	(0.129)	(0.129)	(0.142)	(0.142)
City-fixed effect			yes	yes
R-squared	0.591	0.591	0.637	0.637
N	995	995	995	995
Note:	$^{+}$p<0.15;*p<0.1; **p<0.05; ***p<0.01			

Table 7: Estimates of the price fairness ($CPPF_1$) determinants considering the decomposition of the room rate variability (OLS model with robust standard errors)

	Dependent variable: $CPPF_1$			
	(1)	(2)	(3)	(4)
Dynamic Pricing				
Room rate	-0.438***	-0.437***	-0.426***	-0.425***
	(0.018)	(0.018)	(0.019)	(0.019)
RVr	-0.155	-0.293*	-0.083	-0.247+
	(0.118)	(0.163)	(0.111)	(0.153)
RVw	-0.341**	-0.316*	-0.294**	-0.323*
	(0.142)	(0.185)	(0.136)	(0.169)
RVd	0.284	0.015	0.126	0.004
	(1.505)	(1.431)	(1.340)	(1.218)
RVr * three stars		0.287		0.342+
		(0.231)		(0.218)
RVw * three stars		-0.053		0.056
		(0.288)		(0.275)
RVd * three stars		1.729		1.451
		(4.936)		(4.599)
Breakfast	-0.033	-0.035	-0.049*	-0.051*
	(0.030)	(0.030)	(0.029)	(0.030)
Free cancellation	-0.015	-0.014	0.003	0.006
	(0.028)	(0.028)	(0.027)	(0.027)
Hotel Characteristics				
Three star	0.089***	0.069***	0.101***	0.074***
	(0.017)	(0.025)	(0.017)	(0.025)
Mountain	-0.100***	-0.100***	-0.091**	-0.093**
	(0.023)	(0.023)	(0.039)	(0.039)
Room diversity	-0.007**	-0.007**	-0.007**	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
Room size	0.096***	0.097***	0.112***	0.114***
	(0.032)	(0.032)	(0.028)	(0.028)
Parking	-0.014	-0.014	-0.044***	-0.045***
	(0.015)	(0.015)	(0.016)	(0.016)
Guest Characteristics				
Review	0.001**	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.051***	0.051***	0.052***	0.052***
	(0.018)	(0.018)	(0.018)	(0.018)
Foreign	0.041**	0.041**	0.037**	0.036**
	(0.016)	(0.016)	(0.016)	(0.016)
Constant	2.250***	2.245***	2.045***	2.040***
	(0.129)	(0.129)	(0.142)	(0.143)
City-fixed effect			yes	yes
R-squared	0.590	0.589	0.636	0.636
N	995	995	995	995
Note:	$^{+}$p<0.15; *p<0.1; **p<0.05; ***p<0.01			

Table 8: Tobit estimates of the price fairness ($CPPF_2$) determinants (with robust standard errors)

	Dependent variable: $CPPF_2$			
	(1)	(2)	(3)	(4)
Dynamic Pricing				
Room rate	-0.350***	-0.348***	-0.365***	-0.363***
	(0.017)	(0.017)	(0.018)	(0.018)
Total Rate var.	-0.221***	-0.332***	-0.169**	-0.295***
	(0.080)	(0.110)	(0.078)	(0.101)
Total Rate var. * three stars		0.247+		0.281*
		(0.158)		(0.156)
Breakfast	-0.045+	-0.049*	-0.062**	-0.065**
	(0.028)	(0.028)	(0.027)	(0.027)
Free cancellation	-0.016	-0.014	0.002	0.005
	(0.026)	(0.026)	(0.026)	(0.026)
Hotel characteristics				
Three star	0.075***	0.049**	0.072***	0.043*
	(0.016)	(0.023)	(0.016)	(0.023)
Mountain	-0.074***	-0.075***	-0.084**	-0.087**
	(0.021)	(0.021)	(0.039)	(0.039)
Room diversity	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Room size	0.050*	0.051*	0.074***	0.075***
	(0.027)	(0.027)	(0.026)	(0.026)
Parking	-0.005	-0.005	-0.021	-0.021
	(0.015)	(0.015)	(0.015)	(0.015)
Guest Characteristics				
Review	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.054***	0.054***	0.054***	0.054***
	(0.016)	(0.016)	(0.016)	(0.016)
Foreign	0.031**	0.031**	0.022	0.022
	(0.015)	(0.015)	(0.016)	(0.016)
Constant	1.743***	1.739***	1.728***	1.725***
	(0.122)	(0.122)	(0.124)	(0.124)
City-fixed effect			yes	yes
N	995	995	995	995
Note:	$^{+}$p<0.15; *p<0.1; **p<0.05; ***p<0.01			

Table 9: Tobit estimates of the price fairness ($CPPF_2$) determinants considering the decomposition of the room rate variability (with robust standard errors)

	Dependent variable: $CPPF_2$			
	(1)	(2)	(3)	(4)
Dynamic Pricing				
Room rate	-0.350***	-0.348***	-0.365***	-0.363***
	(0.017)	(0.017)	(0.018)	(0.018)
RVr	-0.180*	-0.354**	-0.111	-0.316**
	(0.106)	(0.156)	(0.105)	(0.146)
RVw	-0.334***	-0.344*	-0.307**	-0.329*
	(0.126)	(0.185)	(0.122)	(0.169)
RVd	0.902	0.596	0.867	0.774
	(1.548)	(1.625)	(1.412)	(1.518)
RVr * three stars		0.365*		0.427**
		(0.209)		(0.207)
RVw * three stars		0.020		0.042
		(0.251)		(0.243)
RVd * three stars		2.286		1.407
		(4.076)		(3.737)
Breakfast	-0.045+	-0.048*	-0.061**	-0.064**
	(0.028)	(0.028)	(0.027)	(0.027)
Free cancellation	-0.015	-0.013	0.003	0.006
	(0.026)	(0.026)	(0.026)	(0.026)
Hotel Characteristics				
Three star	0.076***	0.047**	0.073***	0.040*
	(0.016)	(0.024)	(0.016)	(0.023)
Mountain	-0.074***	-0.074***	-0.084**	-0.088**
	(0.021)	(0.021)	(0.039)	(0.039)
Room diversity	-0.003	-0.003	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Room size	0.051*	0.053*	0.074***	0.076***
	(0.027)	(0.027)	(0.026)	(0.026)
Parking	-0.006	-0.006	-0.022	-0.022
	(0.014)	(0.014)	(0.015)	(0.015)
Guest Characteristics				
Review	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.054***	0.054***	0.054***	0.054***
	(0.016)	(0.016)	(0.016)	(0.016)
Foreign	0.031**	0.031**	0.022	0.021
	(0.015)	(0.015)	(0.016)	(0.016)
Constant	1.740***	1.734***	1.731***	1.725***
	(0.122)	(0.122)	(0.125)	(0.125)
City-fixed effect			yes	yes
N	995	995	995	995
Note:	$^{+}p<0.15$; $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

5. Conclusions

5.1. Summary of results

We have built two measures of the consumer perception of price fairness, based on the difference between the reference price and the price paid by hotel guests using value-for-money score and global score. Three different aspects of dynamic pricing practices have been investigated in order to establish a link between dynamic pricing activity and the loss of price fairness.

First, we considered the impact of dynamic pricing techniques on the room rates paid by hotel guests. We have found that, after controlling for different hotel characteristics, price fairness is negatively related to minimum room-rate levels. This finding implies that dynamic pricing has a major negative impact on price fairness, since dynamic pricing activity leads to higher minimum room rates, especially once cheaper rooms become unavailable (*H3*).

Second, we have also studied the more sophisticated aspects of dynamic pricing, i.e. the change of room rates in relation to room type, week of stay, and booking time. We have implemented a procedure to impute missing information in order to obtain results which are not affected by room-rate unavailability. Then, we computed a measure of the intensity of dynamic pricing practices, given by the overall room-rate variability. We found that, also in this respect, dynamic pricing activity has a negative impact on consumer perception of price fairness (*H1*). This result can be related to the fact that large room-rate differences tend to reduce the reference price, making each price level more unfair [104].

Third, we finally presented a strategy to identify the main components of room-rate variability (room type, week of stay, and booking period) which are more responsible for a negative consumer evaluation. Using a three-way ANOVA decomposition, we found that room type and week-of-stay room-rate variations are the most significant components to explain a drop in consumer perception of price fairness (*H2.1* and *H2.2*).

5.2. Limitations and further research

There are some limitations of our analysis that need to be taken into account.

The first aspect concerns the **data collection strategy**. The sample was made up of 995 hotels located in Italy. Although the focus on a single country has some advantages (e.g. the hotels are more homogeneous), nevertheless, this choice limits the possibility to generalize the results out of this specific, although, relevant geographic area. Similar considerations apply to the choice of the sampling period – which only covers the Summer season – and to the random selection procedure of municipalities in the list of 50-top destinations (see section 3), which have led to an under-representation of lake destinations (e.g. Peschiera, Bardolino, Riva del Garda, Sirmione – ranked 21, 24, 32, 36 respectively – were excluded). Finally, the stratification criteria used to construct the sample (25 three-stars, 15 four-stars and 10 five-stars) could be further extended to also take into account the number of hotels as well as the hotel star distribution at regional level.

Second, **the data.** In order to generalize the results of this study, in addition to Booking.com, further analysis should consider different OTAs and/or the direct hotel website channel. In fact, each channel offers different features, revenue potentials, costs, and degree of controls [see, e.g. 76, 17]. Besides, social media and opaque distribution channels are receiving an increasing interest among hotels to sell their rooms. For instance, opaque channel, such as Hotwire and Priceline models, offers exclusive benefits to hotels that they may even outweigh the high OTA fees [see, e.g. 112]. At hotel level, further variables related to the hotel location – such as its distance from the city center and the number of hotels of the same type close to it – and dimension (i.e. the actual room number and not only its proxy) can be included. At guest characteristic level, further data can be collected accordingly to the recent changes in the information published by Booking.com. For instance, in the guest reviews their number of overnight stay and type of travel are now posted as well.

The econometric model. To investigate the phenomenon of interest, two measures of price fairness are created by leveraging the average customer evaluations in the last two years, while the measures of price variability consider only the summer months. A longer crawling process can be designed so that the timing of the dynamic price strategies actuated fully matches the timing of the customer evaluations. Concerning the imputation method, further statistical techniques can be employed to efficiently impute missing room rates, such as the one proposed in Martín-Fernández et al. [73], Pantanowitz and Marwala [87], Luengo et al. [68], Carota et al. [23]. We believe that, given the specificity of our case, an ad hoc imputation method could be developed to accommodate and include in this process also the dynamic pricing strategies applied by hotels.

5.3. General discussion and implications

Dynamic pricing practices are now widely employed by hotels. However, in this industry there are still many hotels which do not apply such techniques because they worry about negative consumer reactions [55, p. 728]. For example, some of four- and five-star hotels and even more of three-star ones are stuck to an (almost) uniform pricing policy.

Moreover, our analysis shows that consumer perception of price fairness is also influenced by many factors but dynamic pricing. Some of these, such as the (minimum) room rate, free cancellation and other services, are levers directly under the control of hotel manager, while other, such as room characteristics, are not.

Our study on the impact of dynamic pricing activity on perceived price fairness is a first step to identify which are the main aspects in the implementation of dynamic pricing techniques that are less appreciated by consumers, and more critical for firm equity. Our results suggest the following strategic managerial considerations.

First, hotels should focus not only on the short-term but also on the medium-term effects of dynamic pricing activity in order to favor consumer fidelization.

Second, they should limit the extent of the room-rate variability along the room-type and the week-of-stay dimensions, which are more easily observed on booking platforms and, therefore, more responsible for a price fairness reduction.

Third, hotels should avoid too large variations in room-rates not to dilute brand image, provided the negative effect of dynamic pricing on the consumer perception of price fairness. A more cautious use of room-rate strategy plays also in favour of a clearer brand positioning in the market.

Fourth, dynamic pricing practiced by hotels may leave room to a more proactive behaviour of consumers. Prospective buyers can visit the Online Travel Agency platform and monitor the evolution of room-rates in order to get better deals. Alternatively, they can rely on automatic price comparison systems that can help to trace the rate variation and alert consumers when prices decrease [74].

Finally, since dynamic pricing activity tends to be used to respond to an unexpected deviation from a programmed path of sales, hotel managers can get advantage from a more accurate demand forecast in order to reduce useless price variations, which can introduce fairness issues and stimulate the strategic behaviour of consumers.

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Appendices

Appendix A. Sample selection

Tables A.1 - A.4 show a brief summary of the hotels included in the analysis. More specifically, table A.1 presents the city, its geographical position, and the classification according to the location type. Table A.2 reports the number of sampled hotels by city and star-rating category. Some descriptive statistics are provided in table A.4.

Table A.1: Location and type of the sampled hotels

City	Position	Type
Aosta	North	Mountain
Arzachena	South and Islands	Seaside
Cortina d'Ampezzo	North	Mountain
Firenze	Center	Cultural/artistic
Ischia	South and Islands	Seaside
Lignano Sabbiadoro	North	Seaside
Milano	North	Cultural/artistic
Montecatini Terme	Center	Seaside
Napoli	South and Islands	Cultural/artistic
Orbetello	Center	Seaside
Palermo	South and Islands	Cultural/artistic
Perugia	Center	Cultural/artistic
Pisa	Center	Cultural/artistic
Rimini	North	Seaside
Roma	Center	Cultural/artistic
Selva di Val Gardena	North	Mountain
Sorrento	South and Islands	Seaside
Torino	North	Cultural/artistic
Venezia	North	Cultural/artistic
Verona	North	Cultural/artistic
Viareggio	Center	Seaside
Vieste	South and Islands	Seaside

Table A.2: Number of sampled three-, four- and five-star hotels for each city

City	three stars	four stars	five stars
Aosta	30	17	3
Arzachena	25	15	10
Cortina d'Ampezzo	26	20	4
Firenze	25	15	10
Ischia	25	16	9
Lignano Sabbiadoro	25	24	1
Milano	25	15	10
Montecatini Terme	25	22	3
Napoli	25	22	3
Orbetello	28	19	3
Palermo	23	25	2
Perugia	30	18	2
Pisa	23	23	4
Rimini	25	23	2
Roma	25	15	10
Selva di Val Gardena	25	24	1
Sorrento	25	19	6
Torino	25	23	2
Venezia	25	23	2
Verona	27	17	6
Viareggio	29	17	4
Vieste	24	23	3
	565	435	100

Table A.3: Number of three-, four- and five-star hotels for each city used for the analysis

City	three stars	four stars	five stars
Aosta	29	15	3
Arzachena	22	13	10
Cortina d'Ampezzo	23	18	3
Firenze	25	14	9
Ischia	19	14	9
Lignano Sabbiadoro	22	21	1
Milano	25	13	10
Montecatini Terme	17	22	3
Napoli	22	21	3
Orbetello	27	18	2
Palermo	19	24	2
Perugia	27	16	2
Pisa	23	23	4
Rimini	20	22	2
Roma	25	12	8
Selva di Val Gardena	21	20	1
Sorrento	24	17	6
Torino	24	21	1
Venezia	23	21	2
Verona	25	15	5
Viareggio	23	16	4
Vieste	21	20	3
	506	396	93

Table A.4: Number of observations collected for hotels or rooms given for weeks (w) and booking days (d): mean, standard deviation, minimum, maximum and quartiles

	total obs.	count	mean	std	min	1^{st} quart.	median	3^{rd} quart.	max
hotel$\|w$	995	18	758.05	220.28	65	623.5	869	899	952
hotel$\|d$	995	111	613.48	240.10	96	452	596	883.5	975
room$\|w$	5482	18	3145.90	922.98	236	2682.5	3488	3772.25	4150
room$\|d$	5482	111	2394.53	1084.45	397	1554.5	2272	3564.5	4324

Appendix B. Missing values imputation

We propose a method to pre-process data to impute missing values in order to prevent biases in the rate variability. See for a review of imputation methods [66]. This approach is hotel-specific and is based on OLS estimates of the following equation:

$$p_{rwd} = \sum_{r=1}^{R} \beta_r \, D_r + \varepsilon_{rwd}, \tag{B.1}$$

where p_{rwd} indicates the log-price; D_r are the room fixed effects; β_r are the corresponding coefficients; and ε_{rwd} is the error term. Following this approach, we estimate the average room-rate coefficient $\hat{\beta}_r$. In those cases where a rate is missing for a specific room, week of stay, and booking day, we use the following imputation procedure. We search for all the rooms which have a rate in the same week of stay and on the same booking day. Among these, we select the one which has an average room rate closest to that of the room with the missing rate. That room becomes the reference room ρ. Finally, the full set of rates including both existing and imputed ones are obtained as follows:

$$g_{rwd} = \begin{cases} p_{\rho wd} + (\hat{\beta}_r - \hat{\beta}_\rho) & \text{if } p_{rwd} \text{ is not observed} \\ p_{rwd} & \text{otherwise} \end{cases}. \tag{B.2}$$

For a discussion on additive and multiplicative imputation methods see, for instance, [52].

Appendix C. Dynamic pricing decomposition via ANOVA

We summarise the analysis of the variance (a three-way ANOVA) performed on each hotel in the sample . We decompose the dynamic pricing effects on the log-room-rate according to the specified dimensions (room type, week of stay, and booking day) as follows.

Table B.1: Three-way fixed effect ANOVA table specifying the sum of squares (SS) of the first type for each hotel. MS indicates the mean sum of squares obtained as the ratio of the SS and the degrees of freedom (*df*) while F_e indicates the value of the empirical statistic F.

Source of Variability	*SS*	*df*	*MS*	F_e
Model	**SSR**	$R+W+D-3$	MSR	MSR/MSE
Room	SSr	$R-1$	MSr	MSr/MSE
Week of stay	SSw	$W-1$	MSw	MSw/MSE
Booking day	SSd	$D-1$	MSd	MSd/MSE
Error	**SSE**	$n-(R+W+D)+2$	MSE	
Total	**SST**	$n-1$		

Table B.2: Example of a three-way fixed effect ANOVA for a selected hotel h.

Source of Variability	SS	df	MS	F
Model	131.845	45	2.930	488.334
Room	103.387	6	17.231	2819.513
Week of stay	28.168	10	2.817	460.913
Booking day	0.289	29	0.010	1.632
Error	3.997	654	0.006	
Total	132.134	699		