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# Booking in the Rain. Testing the Impact of Public Information on Prices

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## Abstract

Weather forecasts are a rare example of public information which is, at the same time, relevant for agents' decisions and entirely exogenous for both sides of the (tourism) market. We develop a model where signals of good weather have a positive impact on accommodation prices, the effect being stronger the higher the accuracy of the forecast and the ex-ante uncertainty in weather conditions. Using data from a sea and sun destination, we estimate an augmented hedonic price model and find that results robustly support the theory. We also find that the response of prices to weather forecasts is larger for upper-scale hotels than for low- and mid-scale hotels, a result we link to the superior pricing capability of the former.


**Keywords** Information uncertainty · Bayesian model · Pricing strategy · Hotels · Weather forecast · Hedonic price

**JEL Classification** D83 · L11 · L83

## 1 Introduction

Understanding prices and their dynamics is a key issue in economic analysis, as in market economies, the price has the paramount role of allocating resources and conveying information (Hayek 1945). When information is private, the price system uses dispersed knowledge, leading to different degrees of efficiency (Grossman and Stiglitz 1980; Vives 2014). Prices also reflect public information related to external factors

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affecting demand or supply conditions (Bernhardt and Taub 2015). At the business level, strategies of price discrimination and dynamic pricing are nowadays very popular to capture idiosyncratic variations in demand and to provide suppliers with complex but effective tools for revenue management optimization (Alderighi et al. 2022; Bigne et al. 2021; Nocke and Peitz 2007; Moller and Watanabe 2010; Gershkov and Moldovanu 2012; Moller and Watanabe 2016; Neubert 2022; Talón-Ballestero et al. 2022; Vives and Jacob 2021).

Within this general framework, this article aims to assess the impact of public information on prices and identify factors that affect the magnitude of the effect. We do this in an environment where information is highly relevant for the exchange and completely exogenous: the one of weather forecasts and hotel prices. The quality of the stay at the destination (particularly when considering leisure activities linked to summer holidays) is expected to depend on weather conditions (Scott and Lemieux 2011; Gomez-Martin 2005; Zirulia, 2016), and so is demand. Weather forecasts thus play an informative role for economic agents in markets characterized by information uncertainty and when purchasing decisions need to be anticipated through advance booking, like in hospitality and travel. Weather forecasts are continuously produced by private and public providers to predict real weather conditions. A peculiarity of weather forecasts is that they are known (or at least easily accessible) to both sides of the market, which rules out, or significantly weakens issues of information asymmetry.

In this setting, two theoretical arguments can predict the impact of weather forecasts on hotel prices. On the one hand, predictions hinging upon the “traditional view” of consumers’ and suppliers’ rationality are straightforward, in that forecast of good (bad) weather should be associated with relatively high (low) prices because of the impact that information has on demand, and consequently on supply (pricing) behavior.

On the other hand, such a conclusion is less uncontroversial if one looks at the expanding literature on the behavioral industrial organization (for a review, see Heidhues and Kőszegi 2018), specifically, the one focusing on “behavioral firms”, i.e., firms deviating from the typical benchmark of profit maximization. While, in principle, prices should reflect all relevant and available information regarding a specific good or service, there may be behavioral mechanisms that prevent firms from implementing optimal pricing policies. This is the case, for instance, of managerial inertia, advocated by DellaVigna and Gentzkow (2019) as the primary explanation for uniform prices across most US food drugstores and mass-merchandise chains.[1] In this context, managers seem to be rationally bounded and change prices according to rules of thumb based on a subset of state variables rather than setting the optimal price given the information available at each moment. Huang (2021) finds a considerable degree of pricing frictions among Airbnb sellers, as for most of them, prices are sticky over time and uniform across nights of stay. It turns out that both sellers’ price-adjustment costs and their cognitive constraints drive the frictions, the latter being relatively more

[1] Uniform prices have also been documented by Gopinath et al. (2011) and Nakamura and Steinsson (2008) for grocery chains, and by Orbach and Einav (2007) in the movie-theatre industry. Along these lines, Adams and Williams (2019) report limited zone pricing in the home-improvement industry, whereas Melis and Piga (2017) find limited adjustments in hotels’ online pricing behaviour. Ellison et al. (2018) also document pricing inertia and managerial frictions by studying pricing decisions of a set of rival firms selling computer components in an online marketplace.

important. In that respect, the managerial literature argues that pricing should be seen as a capability. To develop the ability to set the right prices, a firm must invest in resources and routines (Dutta et al. 2003).

Within this framework, our contribution is both theoretical and empirical. On the theoretical side, we formalize the "traditional view" and develop a model of flexible prices adopting a Bayesian rational choice approach, where the value of actions stemming from individual decisions depends on realized weather conditions (Katz and Murphy 1997; Tena and Gómez 2011; Zirulia 2016; Raymond and Taylor 2021). The results when prices are flexible are then compared to those obtained assuming inflexible prices. From the theoretical analysis, we derive four hypotheses. First, we expect that bad weather forecasts have a negative effect on prices via the impact they exert on demand. Second, we expect that such an impact is larger the higher the forecast's level of accuracy since information is more valuable for consumers in this case. Third, for the same reason, we expect the impact to be stronger the higher the ex-ante level of uncertainty in weather. Finally, we expect the impact of weather forecasts to be stronger the higher the level of consumers' willingness to pay, given the larger incentive to invest in pricing capability in this case.

We test such theoretical predictions in our empirical contribution. We estimate a hedonic price model augmented with characteristics related to dynamic pricing strategies and weather forecasts to assess the impact of weather forecasts on hotel prices. This approach allows us to tackle the complexity of markets in which price adjustments can be, in principle, almost instantaneous. We use a Big Data approach by collecting data through a web scraper and analyzing daily prices for every hotel offering rooms on Booking.com in our selected destination. Data are then merged with weather forecasts available when prices were posted.

We investigate Rimini (Italy), a typical sea & sun summer destination thereby highly dependent on weather conditions. Given its importance as a mass tourism destination,[2] it is undoubtedly a valuable case study at the international level for empirically validating our hypotheses. The dataset includes the universe of rooms offered by hotels in Rimini on Booking.com, an important search and reservation engine, from June to September 2015. These rooms accrue from a total of 880 hotels. The hotel sector relies heavily on dynamic pricing strategies, hence providing a more meaningful detection of how service providers instantaneously adjust to changes in demand than other segments of the accommodation industry, such as Airbnb (Gibbs et al. 2018; Huang 2021).

### 1.1 Related Literature

Our analysis concerns the impact of public information on prices and, more generally, on economic outcomes and behavior. For this reason, it contributes to several related streams of literature.

[2] In the pre-pandemic age, Rimini and its province used to host about 2.5 million arrivals and 15 million overnight stays every year, 24% of which were foreign tourists in the period June–September 2015 (Unioncamere Emilia-Romagna, 2015).

First, there is vast empirical literature investigating the role of public information and media in various economic settings. In particular, a few studies have analyzed the impact of public information on the stock market (Cutler et al. 1989; Mitchell and Mulherin 1994; Engelberg and Parsons 2011) and in future markets such as those related to crops and livestock (Dorfman and Karali 2015). Information by media companies has been shown to affect corporate governance (Dyck et al. 2008) and political behavior (DellaVigna and Kaplan 2007). Our novel setting presents a few advantages compared to most of the existing literature: (1) the channel through which the information impacts the economy is easy to identify; (2) the accuracy of the information can be measured precisely; (3) the cost to access information, for both firms and consumers, is low so that rational inattention (Sims 2003) does not seem a relevant issue; (4) information is less biased than in situations where political ideology (Gentzkow and Shapiro 2010) or conflicts of interest (Gurun and Butler 2012) are relevant, as suggested by Gentzkow and Shapiro (2006) (although Silver (2012) and Raymond and Taylor (2021) do find some degree of media bias for weather forecasts as well).

On the theory side, our model is related to the literature analyzing the use of information in contexts where strategically interacting agents have access to public and private information (Morris and Shin 2002; Angeletos and Pavan 2007; Myatt and Wallace 2015; Arato et al. 2021).

Our work also contributes to the growing literature on the impact of weather on the economy (a comprehensive survey is provided by Dell et al. 2014). Weather can affect the economy in several ways. It can be an exogenous trigger of economic shocks, leading to a shortage of goods and price increases (Heinen et al. 2018). It can affect the psychological dimension of decision-making in choices ranging from financial investment (Saunders 1993; Hirshleifer and Shumway 2003) to college enrollment (Simonsohn, 2009). It can affect demand indirectly, as is the case for energy (Mu 2007).[3] Finally, it can directly influence the quality of the good or service and, therefore, demand, as is the case for tourism (Shih et al. 2009; Day et al. 2013; Ridderstaat et al. 2014) or wine production (Ashenfelter 2008). More closely related to our article, there is also a (primarily interdisciplinary) literature on the role of weather forecasts in the economy. On the theory side, the seminal work of Nelson and Winter (1964) is the first to study the weather forecasting system through the lenses of Bayesian updating. However, these authors do not consider the interaction between the supply and the demand side of the market, nor the subsequent literature does. Since then, several developments and applications have been proposed, looking at the overall impact of weather forecasts (Katz and Murphy 1997) or in specific sectors, such as agriculture (Mjelde and Penson 2000), energy (Considine et al. 2004) and fishery (Costello et al. 1998). To the best of our knowledge, this study is the first one looking at the impact of weather forecasts on hotel prices.

The remainder of the article is organized as follows. Section 2 presents the model and derives its main predictions. Section 3 introduces the methodology and the data used in the empirical analysis. Section 4 presents the econometric results, whereas

[3] An impact of weather conditions on demand is also found by Cellini and Cuccia (2019) for museum attendance. In this case, weather effects are nonlinear and differ across seasons.

Sect. 5 concludes and discusses the general implications of our work, together with its limitations.

## 2 The Model

In this section, we first formalize the traditional view recalled above in the Introduction by developing a model where prices are flexible to the information provided by weather forecasts. We then compare the results with those obtained assuming inflexible prices, as Zirulia (2016) analyzed. Theoretical findings will be highlighted in four propositions, on which the hypotheses tested in the empirical sections are built.

### 2.1 A Model of Flexible Prices

The model is inspired by the literature analyzing Bayesian decision-making under weather uncertainty and the availability of weather forecasts (Tena and Gómez 2011; Katz and Murphy 1997; Zirulia 2016).

There are two sets of agents: (1) consumers and (2) a firm acting as a monopolist in the market. The monopoly structure assumes market power, which characterizes firms offering sufficiently differentiated services such as accommodation, abstracting at the same time from the complication that emerges when competitive environments are considered. Assuming market power is crucial in our analysis, as it allows the firm to react to information through price adjustments. At the same time, we ignore the effect of competition because the nature of shocks affects competing firms likewise.[4]

Consumers have a heterogeneous willingness to pay for the product sold by the firm, and willingness to pay also depends on external factors, such as weather conditions (Candela and Cellini 1998). Both firms and consumers observe weather forecasts; hence, the price set by the firm is contingent on the weather forecast. Consumers make their choices by observing the posted price and the weather forecast. The details of the demand and the supply sides of the model are described in the following two subsections.

### 2.2 Demand

$\theta_i$ denotes the willingness to pay of consumer $i$ when the weather state is "good". $\theta$ is uniformly distributed across consumers over the support $[\underline{\theta};\overline{\theta}]$, with $1 < \overline{\theta} < 2$, $\overline{\theta} - \underline{\theta} = 1$, and mass normalized to 1. A good weather state may correspond to sunny days for a weekend in a seaside destination, a clear sky and warm temperature for an open-air concert, or a sunny day with natural snow in a ski resort. When the weather state is "bad", the willingness to pay is reduced to $\alpha\theta$ with $0 < \alpha \leq 1$. The individual demand function is discrete: the consumer either buys the product or not. Defining $p$ as the market price, the consumer net utility function is $u = \theta - p$, when the weather state is good, whereas it is $u = \alpha\theta - p$, when the weather state is bad. Her reservation utility is normalized to 0 so that the consumer does not buy when her utility is negative.

[4] See footnote 8 below for a further elaboration of this point.

The purchasing decision is taken before the weather state is realized, based on the probability distribution of weather conditions. Consumers have access to two pieces of information. First, they know the ex-ante probability of a good state, which is $\frac{1}{2} \le r < 1$ (the state is bad with complementary probability).[5] Such a probability is common knowledge among consumers and the firm: it can be interpreted as the historical frequency of "good" and "bad" weather in a specific season. In addition, consumers access the weather forecast, a public signal of the real weather conditions; the signal is correct with a probability $\frac{1}{2} \le q < 1$,[6] and it conveys valuable information to consumers, except in the extreme case of random information, $q = ½$. As a matter of notation, we will use $g$ and $b$ to denote the realized good and bad states, "$g$" and "$b$" to denote the corresponding signals, and $p_{\text{“}g\text{”}}$ and $p_{\text{“}b\text{”}}$ the prices conditional to, respectively, good and bad signals.

By straightforward application of the Bayes theorem, we obtain:

$$\Pr(b|\text{“}b\text{”}) = \frac{(1-r)q}{(1-r)q + r(1-q)} \tag{1}$$

$$\Pr(g|\text{“}b\text{”}) = \frac{r(1-q)}{(1-r)q + r(1-q)} \tag{2}$$

$$\Pr(g|\text{“}g\text{”}) = \frac{rq}{rq + (1-r)(1-q)} \tag{3}$$

$$\Pr(b|\text{“}g\text{”}) = \frac{(1-r)(1-q)}{rq + (1-r)(1-q)} \tag{4}$$

Given such ex-post probabilities on weather states, we can write the consumer's expected utility when buying the product, conditional on the signals received:

$$E(u|\text{“}g\text{”}) = \frac{rq}{rq + (1-r)(1-q)}\theta + \frac{(1-r)(1-q)}{rq + (1-r)(1-q)}\alpha\theta - p_{\text{“}g\text{”}} \tag{5}$$

$$E(u|\text{“}b\text{”}) = \frac{(1-r)q}{(1-r)q + r(1-q)}\alpha\theta + \frac{r(1-q)}{(1-r)q + r(1-q)}\theta - p_{\text{“}b\text{”}} \tag{6}$$

Conditional on "$g$", the consumer buys the product when the expected utility is larger than or equal to 0. This is the case if:

$$\frac{rq}{rq + (1-r)q}\theta + \frac{(1-r)(1-q)}{rq + (1-r)(1-q)}\alpha\theta - p_{\text{“}g\text{”}} \ge 0 \tag{7}$$

Condition (7) determines a threshold $\hat{\theta}_{\text{“}g\text{”}} \equiv \frac{p_{\text{“}g\text{”}}[rq+(1-r)(1-q)]}{rq+\alpha(1-r)(1-q)} = p_{\text{“}g\text{”}}\beta_{\text{“}g\text{”}}$ such that the consumer buys the product if and only if her willingness to pay is larger than,

[5] Assuming that the good state is *ex-ante* more likely than the bad state is theoretically inconsequential, but it simplifies the proof, and it is consistent with the empirical application. In particular, the assumption is used only when we bring to the data the model implication on the role of *ex-ante* uncertainty.

[6] We assume that also $q$ is common knowledge, ruling out disagreement over signal precision (Au 2016).

or equal to, $\hat{\theta}_{\text{"}g\text{"}}$. Similarly, conditional on *"b"*, the consumer buys the product when the expected utility is larger than, or equal to, 0. This is the case if:

$$\frac{(1-r)q}{(1-r)q+r(1-q)}\alpha\theta+\frac{r(1-q)}{(1-r)q+r(1-q)}\theta-p_{\text{"}b\text{"}}\geq 0 \tag{8}$$

Condition (8) determines a threshold $\hat{\theta}_{\text{"}b\text{"}}\equiv\frac{p_{\text{"}b\text{"}}[(1-r)q+r(1-q)]}{r(1-q)+\alpha(1-r)q}\equiv p_{\text{"}b\text{"}}\beta_{\text{"}b\text{"}}$ such that the consumer buys the product if and only if her willingness to pay is larger than, or equal to, $\hat{\theta}_{\text{"}b\text{"}}$.

It can be shown that $\hat{\theta}_{\text{"}g\text{"}}\leq\hat{\theta}_{\text{"}b\text{"}}$, i.e., $\beta_{\text{"}g\text{"}}\leq\beta_{\text{"}b\text{"}}$, where the inequality is strict if $\alpha<1$. In fact,

$$\frac{rq+(1-r)(1-q)}{rq+\alpha(1-r)(1-q)}\leq\frac{(1-r)q+r(1-q)}{r(1-q)+\alpha(1-r)q} \tag{9}$$

simplifies to $r(1-r)(1-\alpha)(1-2q)\leq 0$, which is always satisfied. Intuitively, a good signal induces the purchase even for those consumers with a relatively low willingness to pay; or equivalently, demand is less responsive to price when the ex-post likelihood of good weather increases.

Given $\theta$ distribution, the demand functions, conditional on the signals, are derived by noting that $\Pr\left(\theta\geq\hat{\theta}_{\text{"}g\text{"}}\right)=\overline{\theta}-\hat{\theta}_{\text{"}g\text{"}}$ and $\Pr\left(\theta\geq\hat{\theta}_{\text{"}b\text{"}}\right)=\overline{\theta}-\hat{\theta}_{\text{"}b\text{"}}$:

$$D_{\text{"}g\text{"}}\left(p_{\text{"}g\text{"}}\right)=\overline{\theta}-\hat{\theta}_{\text{"}g\text{"}}=\overline{\theta}-\frac{p[rq+(1-r)(1-q)]}{rq+\alpha(1-r)(1-q)}=\overline{\theta}-\beta_{\text{"}g\text{"}}p_{\text{"}g\text{"}} \tag{10}$$

$$D_{\text{"}b\text{"}}\left(p_{\text{"}b\text{"}}\right)=\overline{\theta}-\hat{\theta}_{\text{"}b\text{"}}=\overline{\theta}-\frac{p[(1-r)q+r(1-q)]}{r(1-q)+\alpha(1-r)q}=\overline{\theta}-\beta_{\text{"}b\text{"}}p_{\text{"}b\text{"}} \tag{11}$$

where $\beta_{\text{"}g\text{"}},\beta_{\text{"}b\text{"}}\in[1,+\infty)$ are the slopes of the linear demand functions.

### 2.3 Supply and Market Equilibrium

The firm operates at zero marginal and fixed costs and chooses its prices to maximize profits (or, equivalently, revenues) after observing the signal. Conditional on good and bad signals, profits are respectively $\Pi_{\text{"}g\text{"}}=p_{\text{"}g\text{"}}D_{\text{"}g\text{"}}\left(p_{\text{"}g\text{"}}\right)$ and $\Pi_{\text{"}b\text{"}}=p_{\text{"}b\text{"}}D_{\text{"}b\text{"}}\left(p_{\text{"}b\text{"}}\right)$. The first-order conditions for profit maximization are:[7]

$$\overline{\theta}-2\beta_{\text{"}g\text{"}}p_{\text{"}g\text{"}}=0 \tag{12}$$

$$\overline{\theta}-2\beta_{\text{"}b\text{"}}p_{\text{"}b\text{"}}=0 \tag{13}$$

[7] Second-order conditions are obviously satisfied.

from which we derive the pair of equilibrium prices, $p^*_{\text{``}g\text{''}} = \frac{\overline{\theta}}{2\beta_{\text{``}g\text{''}}}$ $p^*_{\text{``}b\text{''}} = \frac{\overline{\theta}}{2\beta_{\text{``}b\text{''}}}$, and profits, $\Pi^*_{\text{``}g\text{''}} = \frac{\overline{\theta}^2}{4\beta_{\text{``}g\text{''}}}$ and $\Pi^*_{\text{``}b\text{''}} = \frac{\overline{\theta}^2}{4\beta_{\text{``}b\text{''}}}$. In equilibrium, demand is equal to $\overline{\theta}/2$, irrespectively of the signal. Computing expected profit yields $E\Pi^* = \frac{\overline{\theta}^2}{4}[r + (1-r)\alpha]$, so that expected profits are independent of the level of accuracy. This result comes from the symmetric information between the two parties with respect to the signal, together with perfectly flexible prices on the firm's side.[8]

### 2.4 Discussion and testable implications

This section aims to derive the model implications on the impact of public information on equilibrium prices, which will then be tested in Sect. 4. Specifically, we look at the impact of information provided by weather forecasters (good *vs* bad signal) both in absolute and percentage terms. By defining $\Delta p^* \equiv p_{\text{``}g\text{''}} - p_{\text{``}b\text{''}}$ and $\%\Delta p^* \equiv \left(p_{\text{``}g\text{''}} - p_{\text{``}b\text{''}}\right)/p_{\text{``}b\text{''}}$, straightforward computations yield:

$$\Delta p^* = \frac{\overline{\theta}}{2}\left(\frac{1}{\beta_{\text{``}g\text{''}}} - \frac{1}{\beta_{\text{``}b\text{''}}}\right) = \frac{\overline{\theta} r(1-r)(2q-1)(1-\alpha)}{2[rq + (1-r)(1-q)][(1-r)q + r(1-q)]} \tag{14}$$

$$\%\Delta p^* = \frac{\beta_{\text{``}b\text{''}}}{\beta_{\text{``}g\text{''}}} - 1 = \frac{[rq + (1-r)(1-q)]}{rq + \alpha(1-r)(1-q)} \frac{[\alpha(1-r)q + r(1-q)]}{r(1-q) + (1-r)q} - 1 \tag{15}$$

From inspection of (14), it is immediate to see that $\Delta p \geq 0$ (as $q \geq \frac{1}{2}$), from which $\%\Delta p^* \geq 0$ follows. In other words:

**Proposition 1** *A forecast of good weather has a positive impact on price, both in absolute and percentage terms.*

The result can be interpreted in terms of the elasticity rule, which is typical of monopoly pricing. Demand elasticities are defined as $\beta_{\text{``}g\text{''}} \frac{p_{\text{``}g\text{''}}}{D_{\text{``}g\text{''}}(p_{\text{``}g\text{''}})}$ and $\beta_{\text{``}b\text{''}} \frac{p_{\text{``}b\text{''}}}{D_{\text{``}b\text{''}}(p_{\text{``}b\text{''}})}$. In equilibrium, their value is 1 (being marginal cost nil). As demand is constant at equilibrium, prices are inversely related to the value taken by $\beta_{\text{``}g\text{''}}$ and $\beta_{\text{``}b\text{''}}$: signals that increase the *ex-post* likelihood of a good state reduce the sensitiveness of consumers to prices, and the firm reacts by increasing the price.

The second set of predictions derived from the model concerns those factors that can affect the magnitude of $\Delta p^*$ and $\%\Delta p^* \geq 0$. In particular, we look at how the precision of the information, i.e., the weather forecasts' accuracy and the ex-ante

[8] While a full-fledged analysis of competition would require a different formulation of consumers' utility function, a simple way to account for it would be to consider a firm demand function (contingent to weather forecasts) as $D(p) = \overline{\theta} - \beta p - \gamma(p - \overline{p})$. In this formulation, $\overline{p}$ stands for the average price of the competitors, which acts as a reference price (Viglia et al., 2016). In a monopolistic competitive equilibrium with symmetric prices, the average price would be equal to equilibrium price for each firm. It can be shown that the impact of $\beta$ on price would not be affected, and as easily expected, a higher value of $\gamma$ would have a negative impact on the price. This claim is supported by the extension of the model to a duopoly regime with vertical differentiation, which yields predictions in line with those reported in this article. Details are available upon request.

level of uncertainty, mediates the extent of price variation. In the model, precision is measured by $q$, whereas uncertainty is inversely related to $r$ (if $r \geq \frac{1}{2}$ as we assumed).

**Proposition 2** *The more accurate the weather forecasts (i.e., the larger $q$), the larger the impact of a good weather forecast on price, both in absolute and percentage terms.*

**Proposition 3** *The higher the ex-ante level of weather uncertainty (i.e., the lower $r$), the larger the impact of a good weather forecast on price, both in absolute and percentage terms.*

Proofs of Propositions 2 and 3 are in Appendix 1. The interpretation of Proposition 2 is straightforward: the more accurate the signals, the higher the value of conveyed information. Once again, the effect unfolds on-demand elasticity since more reliable forecasts make demand less elastic when the signal is good (thus leading to a price increase) and more elastic when the signal is bad (thus reducing price).

As for Proposition 3, the intuition is that when ex-ante uncertainty is high, informative signals embodied by weather forecasts have a stronger impact on the ex-post assessment of the probability of good and bad weather. Consequently, a forecast of good weather significantly reduces demand elasticity, and the opposite occurs for a forecast of bad weather.

### 2.5 Flexible vs. Inflexible Prices

Zirulia (2016) analyzes a model where the demand side is the same as the previous section, but the firm is constrained to fix a single price.[9] Therefore, the firm chooses its price to maximize its expected profits before the signal is observed:

$$E\prod = [rq + (1-r)(1-q)]pD_{\text{``}g\text{''}}(p) + [(1-r)q + r(1-q)]pD_{\text{``}b\text{''}}(p) = pED(p) \tag{16}$$

from which the equilibrium price is obtained:

$$p^* = \frac{\overline{\theta}}{2\left\{\beta_{\text{``}g\text{''}}[rq + (1-r)(1-q)] + \beta_{\text{``}b\text{''}}[r(1-q) + (1-r)q]\right\}} \tag{17}$$

and, consequently, the equilibrium level of expected profit:

$$E\Pi^* = \frac{\overline{\theta}^2}{4}\left\{\frac{1}{\frac{[rq+(1-r)(1-q)]^2}{[rq+\alpha(1-r)(1-q)]}} + \frac{1}{\frac{[r(1-q)+(1-r)q]^2}{[r(1-q)+\alpha(1-r)q]}}\right\}. \tag{18}$$

[9] As a matter of fact, Zirulia (2016) considers the case $\overline{\theta} = 1$, but extending to $\overline{\theta} \neq 1$ is trivial. The reader is referred to that paper for further details.

The difference in expected profit between the flexible and inflexible case is thus given by:

$$\Delta E\Pi^* = \frac{\overline{\theta}^2}{4}\left\{[r + (1-r)\alpha] - \frac{1}{\frac{[rq+(1-r)(1-q)]^2}{[rq+\alpha(1-r)(1-q)]}} + \frac{1}{\frac{[r(1-q)+(1-r)q]^2}{[r(1-q)+\alpha(1-r)q)]}}\right\} \tag{19}$$

Zirulia (2016) shows that $E\Pi^*$ is decreasing in $q$ in when prices are inflexible: the more accurate the weather forecasts, the larger the advantage for consumers when choosing after observing the weather signal. This analysis shows that $E\Pi^*$ is independent of $q$ when prices are flexible. It is immediate to show that $\Delta E\Pi^* = 0$ at $q = \frac{1}{2}$, which implies $\Delta E\Pi^* \geq 0$ for $q \geq \frac{1}{2}$. Price flexibility yields additional profit to the firm because it posits a symmetric situation between the firm and the consumers. In contrast, with inflexible prices, consumers decide knowing more than the firm about the weather state. Inspection of (19) also reveals that $\Delta E\Pi^*$ is increasing in $\overline{\theta}$, from which the fourth and last proposition is derived.

**Proposition 4** *The higher the level of consumers' willingness to pay (i.e., the higher $\overline{\theta}$), the larger the impact of flexible prices (vs. inflexible prices) on expected profit.*

## 3 Data, methodology, and hypotheses formulation

### 3.1 Data

Data have been collected through a scraper in the summer (June–September 2015) for Rimini, an important Italian sea and sun destination. Rimini and its province hosted more than 2.5 million arrivals and 15 million overnight stays per year in the pre-pandemic years. This city has been chosen because of its relevance in the tourism sector and because, in the summer season, the town hosts leisure tourists who generally spend the day on the beach. Arguably, they are susceptible to weather conditions (De Freitas 2015).[10] Data come from the 880 Rimini hotels (or similar accommodations) offering rooms online in our sample period. Most hotels have a 3-star classification (493), followed by 2-star hotels (126), 4-star hotels (79), 1-star hotels (20), and 5-star hotels (2).[11] The hotels with a star classification in our sample represent about 73% of the entire universe of Rimini hotels. The clientele in Rimini consists of a vast majority of domestic (Italian) tourists, accounting for 76% of total arrivals in summer 2015.

Each day the scraper collected information on (1) hotel prices and other characteristics, posted daily on Booking.com, an important hotel reservation website; (2) weather forecasts from the most popular—commercial—weather website/app; (3) actual weather conditions from a public archive. Accordingly, we use a Big Data

[10] In 2015, the period July–September accounted for 78% of overall arrivals in Rimini. Coherently with this summertime specialization, most hotels are located close to the sea along the 16 km Rimini coast.

[11] The remaining hotels are not classified, typically being establishments that are not officially classified as hotels (e.g., hostels or residential structures).

approach, as our dataset comprises two out of the three categories of big data applied to the tourism sector (Li et al. 2018): UGC data (data generated by users, such as ratings, in our case), and transaction data (online web searches and booking data).[12]

i. *Hotel prices and other characteristics* The first part of the database contains the hotel prices posted daily on Booking.com for the whole population of hotels in Rimini that offered rooms on this website. The scraper searched prices for one-week stays (from Saturday to Saturday) and short weekend breaks (a two-night stay, from Friday to Sunday) in the period 29 May (Friday) to 26 September (Saturday) as check-in dates. A 15-day lead booking period was considered (that is, for each search, prices posted up to 15 days before the check-in date were collected) to match prices and weather forecasts. The whole set of available rooms and price conditions on offer were scraped. Names, labels, and descriptive statistics of the variables are reported in Table 4 in Appendix 2.
ii. *Weather forecasts* The scraper collected weather forecasts published by the most popular commercial website/app in Italy: ilmeteo.it, an application with more than 10 million downloads on Google Play Store alone. Despite the availability of several other websites and apps, the popularity of this service makes it the most important influencer for weather forecasts in Italy, and its bulletins are regularly reposted and published by national newspapers and popular media. Table 5 in Appendix 2 compares weather forecasting apps in Italy and their rating figures, showing the typical J-shaped distribution of rating websites (Hu et al. 2009). Each day, from 13 May to 27 September, the scraper collected information on forecasts for Rimini for the following 15 days. Forecasts included the minimum and maximum temperature and the literal translation of the icon summarizing the overall weather for the forecast day (sunny/ rainy/ cloudy/ etc.). Net of the missing forecasts due to unavailability of the scraper or the website, 1,942 observations were collected, with the main summary statistics reported in Tables 6 and 7 in Appendix 2.
iii. *Actual weather conditions* Data on actual weather conditions, as recorded by the official public archive (Arpa-ER, the Regional Agency for Environmental Protection), were also collected to assess the accuracy of forecasts. Archived data included the millimeters of rain, air pressure, maximum, minimum, and daily average temperature, maximum, minimum and daily average humidity, wind speed and direction. The summary statistics for these variables in the period under investigation are reported in Table 8 in Appendix 2.

After a complex cross-check, some inconsistent observations were deleted, leaving about 730,000 observations for the statistical and econometric analysis. Further information about the construction of the dataset is reported in Appendix 2.

### 3.2 Methodology and Hypotheses Formulation

A hedonic price model was estimated. Differently from standard hedonic models, in which only the physical quality characteristics of the product are considered, the price

[12] The remaining category consists of device data (GPS, Bluetooth), but this information is not relevant for our study.

was also regressed over a set of "dynamic characteristics", i.e., characteristics that vary over time (number of available rooms, booking lead time, weather forecasts, etc.). This is in line with the recent empirical literature on hotel dynamic pricing (Abrate et al. 2012; Melis and Piga 2017; Falk and Vieru 2019). We run both a linear and a log-linear version of the model to test hypotheses in terms of both absolute and percentage price variations.

The general specification of the linear model is the following:

$$P_{i,t,t-\tau} = a + bWF_{t,t-\tau} + cD_{i,t} + dBT_{i,t,t-\tau} + eFC_{i,t,t-\tau} + fLT_{t,t-\tau} + gSO_{i,t,t-\tau} + hAR_{i,t,t-\tau} + iKIDS_{i,t,t-\tau} + jLOS_{i,t,t-\tau} + kR_iH_j + \varepsilon_{i,t,t-\tau} \tag{20}$$

where:

- $P_{i,t,t-\tau}$ is the daily price (computed by dividing the posted price over the length of stay) of room *i* for check-in date *t* posted at time $t-\tau$, where $0 \le \tau \le 15$. Hence, $\tau$ represents the time distance between the check-in day and the day when the price and the information about the weather goes public. In log-linear specifications of the model, *lnP*, the natural logarithm of price, was alternatively used as the dependent variable.
- $WF_{t,t-\tau}$ is the main variable of interest and is a set of dummies built over the variable *Weather Forecast code* reported in Table 7, controlling for the weather forecast for time *t* posted at time $t-\tau$. In some of the alternative specifications of the model, $WF_{t,t-\tau}$ is proxied by *No_rain*, or *Sun*, binary variables built by aggregation of the different values of *Weather Forecast code*. More specifically, *No_rain* (*Sun*) takes the value of 1 if *the Weather Forecast code takes* 1, 2, or 3 (1 or 2) as indicated in Table 7, and 0 otherwise.[13]
- $D_{i,t}$ is a set of dummies built over the variable *Check-in* reported in Table 4, controlling for the different check-in dates.
- $BT_{i,t,t-\tau}$ is a set of dummies built over the variable *Board Type* reported in Table 4, controlling for the type of service included (bed only, bed and breakfast, half-board, half-board with lunch, full-board).
- $FC_{i,t,t-\tau}$ is a dummy variable controlling for the possibility of canceling the booking without penalties (*Free Cancellation*).
- $LT_{t,t-\tau}$ is a numeric variable measuring the *Lead Time*, i.e., the distance between the search date and the check-in date; it is then equal to $t-\tau$ for each observation and controls for the use of dynamic pricing strategies.
- $SO_{i,t,t-\tau}$ is a dummy indicating if the price is advertised as a special offer/discount (variable *Special Offer* in Table 4).
- $AR_{i,t,t-\tau}$ is a set of dummies built over the variable *Available Rooms*, reported in Table 4, controlling for the supply constraint, the number of rooms shown as available on the platform at the posted price (from 1 to 5). When the number of available rooms was more than 5, the variable was coded as 0.

[13] In the sensitivity analysis, alternative proxies for $WF_{t,t-\tau}$ such as the maximum daily temperature (T_max) and the average daily temperature (T_mean) were also tested, providing robust results.

- $KIDS_{i,t,t-\tau}$ is a dummy variable that indicates that the price refers to a room that can accommodate two kids, in addition to two adults.
- $LOS_{i,t,t-\tau}$ is a variable indicating the *Length of Stay*, to control for different price offers for weekends, long weekends, and one-week holidays.
- $R_i$ is a set of dummies built over the variable *Room type* reported in Table 4, controlling for the different characteristics of the rooms, such as size, floor, and sea view.
- $H_j$ is a set of dummies built over the variable *Hotel* reported in Table 4, controlling for the hotels' fixed effects.

The theoretical propositions derived in Sect. 2 lead us to formulate the following four hypotheses.

**Hypothesis 1.** Coherently with Proposition 1, ceteris paribus, good weather forecasts are associated with higher prices.

As regards the proxy for weather, following Scott et al. (2008), we chose the sun/rain indicator (the variable $WF_{t,t-\tau}$ in our dataset), as it is likely to be the most relevant factor associated with beach activities in a sea & sun destination. Using as reference category the most positive forecast ($WF_{t,t-\tau} = 1$), we expect negative coefficients for the other $WF_{t,t-\tau}$ categories, with the coefficients being larger in absolute value for more negative forecasts. In the alternative specifications, in which *No_rain* or *Sun* dummy variables are used, we expect a positive coefficient associated with these variables.

Hypotheses 2 to 4 are tested by running a series of separate regressions.

**Hypothesis 2.** Coherently with Proposition 2, the impact of weather forecasts on prices is stronger the more accurate the forecasts.

In that respect, scientific evidence (Bauer et al. 2015; Alley et al. 2019) shows that forecast accuracy varies with the temporal distance between the day when the forecast is produced, and the day it refers to, i.e., forecast accuracy increases the shorter the time lag of the forecast. Our data corroborate this evidence: a rain forecast fifteen days in advance corresponds to actual rain 73.64% of the time, while the percentage rises to 84.91% when the forecast is produced three days in advance. It follows that the impact of weather forecasts on prices is expected to be stronger the closer the forecasts are to the day of the check-in. In Sect. 4, we compare regressions where only the last three days of the booking period are considered with regressions referring to the complementary period, i.e., 4 up to 15 days in advance.[14] We predict the impact of weather forecasts to be stronger in the former case.

Running separate regressions posits some issues we need to discuss further. First, it is important to stress that we control for time-dependent variables in all our regressions, such as check-in date, lead time, and the number of rooms available on the platform, whose omission would confound the interpretation of weather forecast coefficients. Second, the two sub-samples may differ in terms of demand composition. This would

[14] This split is justified by the choice of the public provider (the Aeronautica Militare in the Italian case), which produces forecasts only over the previous 72 h, to guarantee their reliability.

be problematic if customers booking in the last three days were characterized by a higher willingness to pay (higher $\overline{\theta}$), as this would induce a stronger reaction to weather forecasts in terms of absolute price variation (but with no effect in percentage terms). Business travelers are typically last-minute bookers with a high willingness to pay, but they do not constitute a relevant share of tourists for Rimini in the period under consideration (June–September).[15]

As for systematic differences in the fraction of utility associated with bad weather (i.e., $\alpha$), there are no compelling reasons to think this parameter should differ across booking periods. In addition, variations in $\alpha$ have different impacts on absolute and relative variations, since $\frac{d\Delta p^*}{d\alpha} < 0$ and $\frac{d\%\Delta p^*}{d\alpha} > 0$.

**Hypothesis 3.** Coherently with Proposition 3, the impact of weather forecasts on prices is larger, the higher the weather uncertainty.

In our case, a good proxy for weather uncertainty is the period of the year. According to historical data for Rimini, the average rainfall is lower in the central part of the summer season (July and August) than in the early and late summer months (June and September). For instance, the average monthly rainfall for July and August in the 2011–2015 period was 49.4 mm, while it was 74.4 mm for June and September of the same years.[16] Section 4 compares regressions where only the peak period (July–August) is considered, with regressions for the off-peak period only (June–September). We expect the impact of weather forecasts to be stronger in the former case.

As done for Hypothesis 2, a discussion concerning the composition of the two subsamples is in order. Clearly, the level of demand also varies between July–August (the peak period) and June–September (the off-peak period). However, our theoretical analysis predicts that a higher value of $\overline{\theta}$ (as in the peak compared to the off-peak period) should entail a *stronger* impact of the weather forecast on absolute price variation (with no effect in percentage terms), which would go against Hypothesis 3. Therefore, finding support for our hypothesis would entail that the "weather uncertainty" effect is particularly strong. In addition, there is no reason to think that $\alpha$ should systematically differ across seasons.

**Hypothesis 4.** Coherently with *Proposition 4*, the larger the impact of weather forecasts on prices, the higher the consumers' willingness to pay.

In the business reality, a sophisticated pricing approach enabling firms to adjust to varying market conditions requires a set of investments and skills (including IT infrastructures, an appropriate organizational architecture (Aubke et al. 2014), and a dedicated and competent workforce, Selmi and Dornier 2011) that not all firms may possess. In fact, the cognitive cost of determining the correct timing and size of a price change can be notable (Ellison et al. 2018). Hotel managers also face an

[15] According to Istat (2016) and our subsequent elaboration on Istat data, business trips constitute 14.2% of all travels in Rimini province for 2015, but only 8.1% for the June–September period.

[16] Own elaboration, based on official statistics provided by Arpa-ER – Regional Agency for Environmental Protection Emilia Romagna (simc.arpae.it/dext3r). This evidence is robust to the use of the average monthly number of rainy days, according to which there were 4.9 rainy days in July–August and 7.6 in June and September, for the same years.

opportunity cost of price adjustments since they must devote their attention to several other business decisions (Bergen et al. 2003; Levy et al. 2010). Proposition 4 shows that the additional profit from flexible prices is increasing in consumers' willingness to pay (i.e., increasing in $\overline{\theta}$). Since we can expect 4- and 5-star (upscale) hotels to face customers with a higher willingness to pay, such hotels should have a higher return from investment in pricing capability and so more likely to adopt sophisticated pricing techniques.[17] Consistently with this view, Melis and Piga (2017) find that 4- and 5-star (upscale) hotels are more likely to use dynamic pricing.

Based on these premises, Sect. 4 estimates the hedonic pricing model separately for upper-scale hotels (4- and 5-star hotels) and low- and mid-scale hotels (1-, 2- and 3-star hotels), and we predict the impact of weather forecasts to be stronger in the former case. We also remind that, under the assumption of flexible prices, our theoretical analysis predicts that higher values of $\overline{\theta}$ should be associated with a stronger impact of weather forecasts when measured in absolute terms but independent of scale when the effect is measured in percentage terms. The data, then, can help in discriminating between the two mechanisms.[18]

A final observation concerns the fit of our empirical case study with the theoretical framework. Market structure in the Rimini hotel sector is best represented, in our view, by a monopolistically competitive market form, with many firms competing (so that strategic interaction is not an issue), each of them having some market power. In Sect. 2 (footnote 8 in particular), we argue why our results developed in a monopolistic setting can be extended to competitive settings like Rimini. As for the existence of market power, there is evidence that Rimini hotels are not only differentiated by location, as is commonly observed in the accommodation sector (Lee 2015), but also in terms of services that are offered (Presutti et al. 2020).

# 4 Results

## 4.1 Testing Hypothesis 1: the impact of weather forecasts on hotel prices

The results of testing the first hypothesis are reported in Table 1. As recalled in Sect. 3.2, we regressed the daily price for room $i$ of hotel $j$ for the check-in date $t$ posted at $t-\tau$ on the weather forecast for $t$ posted in $t$—$\tau$ (after controlling for all the other variables included in Eq. (16)).

Model (1.1) of Table 1 reports the results for the most consistent subset of the dataset, where the daily price of one double room for party groups of two adults for a weekend break was regressed. This subsample includes about 92,000 observations. Estimations suggest that *ceteris paribus*, bad weather was significantly associated with lower prices compared to the case of the base category, which is "hot and sunny", the most positive

[17] In our sample, chain hotels play a very limited role, since only 30 establishments were affiliated to chains in Rimini in 2015 (Horwath HTL, 2016). It follows that the mechanism identified in Leisten (2021), for which marginal royalty rates can affect the cost of acquiring information, should not apply to our case.

[18] A priori, the impact of hotel category on $\alpha$ is instead ambiguous, as higher quality hotels offer services that both counter-balance possible negative weather conditions (such as spa services) or stress the importance of good weather conditions (swimming pools, open-air bars, etc.).

**Table 1** Impact of weather forecasts on prices

| | (1.1) P, errors not clustered | (1.2) P, errors clustered | (1.3) lnP, errors not clustered | (1.4) lnP, errors clustered | (1.5) lnP, errors clustered |
|---|---|---|---|---|---|
| WF 2 | − 4.080***[− 4.81] | − 4.080**[− 2.49] | − 0.0463***[− 9.12] | − 0.0463***[− 4.94] | |
| WF 3 | − 3.022***[− 3.89] | − 3.022**[− 2.34] | − 0.0566***[− 12.29] | − 0.0566***[− 6.65] | |
| WF 4 | − 7.196***[− 7.97] | − 7.196***[− 4.14] | − 0.109***[− 18.74] | − 0.109***[− 10.31] | |
| WF 5 | − 7.725***[− 4.61] | − 7.725***[− 2.64] | − 0.0785***[− 10.90] | − 0.0785***[− 5.79] | |
| WF 7 | − 3.395***[− 3.32] | − 3.395**[− 2.18] | − 0.0393***[− 6.54] | − 0.0393***[− 4.22] | |
| WF 8 | − 6.823***[− 3.74] | − 6.823**[− 2.22] | − 0.0449***[− 4.92] | − 0.0449***[− 3.00] | |
| No_rain | | | | | 0.0349***[6.74] |
| Sun | | | | | |
| T_max | | | | | |
| T_mean | | | | | |
| Free cancellation | 3.384***[5.21] | 3.384 [1.29] | 0.0344***[9.88] | 0.0344**[2.53] | 0.0304**[2.24] |
| Lead time | − 1.109***[− 15.49] | − 1.109***[− 4.06] | − 0.00663***[− 16.39] | − 0.00663***[− 5.46] | − 0.00701***[− 5.98] |
| Special offer | − 19.32***[− 39.59] | − 19.32***[− 6.64] | − 0.195***[− 52.56] | − 0.195***[− 11.02] | − 0.190***[− 10.93] |
| Available rooms (1) | 7.573***[9.79] | 7.573*[1.76] | 0.0940***[15.99] | 0.0940***[2.84] | 0.0929***[2.81] |
| Available rooms (2) | 6.522***[8.68] | 6.522 [1.53] | 0.0887***[15.21] | 0.0887***[2.76] | 0.0883***[2.74] |
| Available rooms (3) | 2.842***[3.66] | 2.842 [0.70] | 0.0485***[7.87] | 0.0485 [1.51] | 0.0476 [1.49] |
| Available rooms (4) | 2.891***[3.54] | 2.891 [0.67] | 0.0531***[7.60] | 0.0531 [1.49] | 0.0522 [1.45] |
| Available rooms (5) | 2.201***[2.69] | 2.201 [0.54] | 0.0502***[7.21] | 0.0502 [1.55] | 0.0502 [1.55] |
| Kids | | | | | |
| LOS | | | | | |
| Room type * Hotel | YES | YES | YES | YES | YES |
| Constant | 73.83***[15.03] | 73.83***[9.12] | 3.962***[79.20] | 3.962***[63.29] | 3.907***[63.29] |

**Table 1** (continued)

| | (1.1) P, errors not clustered | (1.2) P, errors clustered | (1.3) lnP, errors not clustered | (1.4) lnP, errors clustered | (1.5) lnP, errors clustered |
|---|---|---|---|---|---|
| *N* | 92,137 | 92,137 | 92,137 | 92,137 | 92,137 |
| adj. $R^2$ | 0.536 | 0.536 | 0.655 | 0.655 | 0.653 |

| | (1.6) lnP, errors clustered | (1.7) lnP, errors clustered | (1.8) lnP, errors clustered | (1.9) lnP, any room, any party | (1.10) lnP, any stay |
|---|---|---|---|---|---|
| WF 2 | | | | | |
| WF 3 | | | | | |
| WF 4 | | | | | |
| WF 5 | | | | | |
| WF 7 | | | | | |
| WF 8 | | | | | |
| No_rain | | | | 0.0370***[19.27] | 0.0124***[3.06] |
| Sun | 0.0362***[6.45] | | | | |
| T_max | | 0.0176***[8.97] | | | |
| T_mean | | | 0.0160***[6.32] | | |
| Free cancellation | 0.0326**[2.41] | 0.0284**[2.10] | 0.0338**[2.49] | 0.0227***[10.21] | 0.0267**[2.23] |
| Lead time | − 0.00739***[− 6.31] | − 0.00541***[− 4.59] | − 0.00836***[− 7.18] | − 0.00574***[− 23.57] | − 0.00362***[− 3.95] |
| Special offer | − 0.190***[− 10.91] | − 0.185***[− 10.58] | − 0.187***[− 10.72] | − 0.199***[− 86.66] | − 0.187***[− 12.74] |
| Available rooms (1) | 0.0930***[2.82] | 0.0941***[2.85] | 0.0935***[2.84] | 0.128***[27.17] | 0.0694**[2.25] |
| Available rooms (2) | 0.0880***[2.74] | 0.0883***[2.75] | 0.0887***[2.76] | 0.109***[23.27] | 0.0779**[2.56] |
| Available rooms (3) | 0.0479 [1.50] | 0.0476 [1.49] | 0.0477 [1.50] | 0.0885***[18.28] | 0.0578**[1.98] |

**Table 1** (continued)

| | (1.6)<br>lnP, errors clustered | (1.7)<br>lnP, errors clustered | (1.8)<br>lnP, errors clustered | (1.9)<br>lnP, any room, any party | (1.10)<br>lnP, any stay |
|---|---|---|---|---|---|
| Available rooms (4) | 0.0512 [1.44] | 0.0529 [1.48] | 0.0521 [1.46] | 0.0921***[18.03] | 0.0362 [1.00] |
| Available rooms (5) | 0.0496 [1.53] | 0.0502 [1.55] | 0.0501 [1.55] | 0.0515***[9.50] | 0.0446 [1.34] |
| Kids | | | | 0.0881***[27.01] | |
| LOS | | | | | − 0.0452 [− 1.48] |
| Room type * Hotel | YES | YES | YES | YES[a] | YES[a] |
| Constant | 3.910***[63.98] | 3.516***[44.51] | 3.625***[45.95] | 3.555***[137.06] | 4.097***[36.60] |
| *N* | 92,137 | 92,137 | 92,137 | 230,092 | 187,505 |
| adj. $R^2$ | 0.653 | 0.655 | 0.654 | 0.638 | 0.658 |

t-statistics in brackets; *p < 0.10; **p < 0.05; ***p < 0.01. Robust errors in all regressions. The dependent variable is price *P* in models (1.1), (1.2) and the logarithm of price *lnP* in the other models. In models (1.2) and (1.4) to (1.10), errors are clustered by hotel. All models except (1.9) include only observations related to a double room for two adults; Model (1.9) includes any combination of rooms for a party group of two adults and two kids. All models except (1.10) include only observations related to a weekend stay of two nights (from Friday to Sunday); Model (1.10) includes all observations related to both weekends and full weeks (from Saturday to Saturday). Controls included in every model: *Check-in dates, Board type*

[a]In models (1.9) and (1.10), hotel dummies and Room type dummies are included without interaction

forecast available on *ilmeteo.it* codification ($WF_{t,t-\tau} = 1$). These findings are hence consistent with Hypothesis 1. As regression (1.1) is linear, the coefficients can be directly interpreted as the price variation between the actual weather forecast and the base "hot and sunny" weather forecast. This "discount" for sub-optimal forecasts ranges between € 4.08 (overcast, code WF 2) to € 7.20 (downpour, code WF 4) and to € 7.73 (cloudy, code WF 5).

All the other variables included in (1.1) are significant at the 1% level and with the expected sign: the free cancellation option was associated with a higher price (of about € 3.38 per day), which could be interpreted as the premium paid for buying the option of disattending the contract.[19] Any day closer to the check-in date was associated with a higher price (of about € 1.11, see specifically the coefficient of *Lead time*), coherently with a strategy of increasing prices when the occupancy rates are high and the check-in dates approach. Special offers have a heavy impact on price: the average discount is estimated to be € 19.32, more than 20% of the basic price in the regression, represented by the constant (€ 73.83). Finally, the indication that there is only a limited number of available rooms on offer is relevant: the coefficients of $AR_{i,t,t-\tau}$ (*Available Rooms*) are positive, suggesting that a constraint from the supply side is associated with a price higher than the base category, in which no signal of limitation in the supply was posted.[20] Coherently with the standard law of demand and supply, the coefficient is the lowest when the available rooms are many (*Available rooms (5)*, € 2.20) and increasing when available rooms decrease, reaching the maximum when the signaled number is 1 (*Available rooms (1),* € 7.57). This is exactly what is expected when the hotel approaches full occupancy.

As regards the other variables included in the regression but omitted from Table 1 for space limitation, the coefficients of the *Check-in dates* (dummies) are all significant and with the expected sign: prices are higher approaching the peak period of late July–mid-August, signaling an active policy of seasonal pricing. Moreover, the coefficients of the interaction dummies between room type and hotel (R*H) are also statistically significant, showing that the overall quality of the hotel and the characteristics of the posted room are also relevant in determining the price, as expected. Overall, the dynamic characteristics of the pricing strategy are essential in explaining the posted price, improving the overall explanatory power of the regression (adjusted R-squared is around 54%) compared to standard hedonic models.

Errors in regression (1.1) are robust but assumed to be uncorrelated across groups. As price dynamics heavily depend on revenue management strategies run by hotels, likely, errors in different periods and for different rooms in a given hotel may be correlated: failure to control for within-cluster error correlation can generate larger t-statistics and more "optimistic" results. Model (1.2) in Table 1 tackles this issue and encompasses clustered errors at the hotel level. As expected, confidence intervals increase, and some of the variables included in the model are no longer significant (e.g., *Available rooms and Free cancellation*), highlighting that hotels apply a common rule regarding these variables. In particular, the cost of breakfast, which is negligible for most of the structures, is likely to allow hotels to manipulate the inclusion of

[19] A similar result was obtained by Escobari and Jindapon (2014) for airlines.

[20] See Courty and Ozel (2019) on the value of online scarcity cues.

the breakfast in the posted price as a kind of promotional strategy. However, more important is that the estimated coefficients for weather forecasts (*WF 2 – WF 8*) in Model (1.2) remain significant.

Table 1 also reports the results of the log-linear model. Specifically, regressions (1.3) and (1.4) include the logarithm of price as the dependent variable, respectively, with robust standard errors (1.3) and robust standard errors clustered by hotel (1.4). Overall, the results are in line with Model (1.1) in terms of sign and significance of the coefficients: weather forecasts worse than the baseline "hot and sunny" are associated with lower prices, from 3.9% of rain (*WF* 7) to 10.9% of downpour (*WF* 4) forecasts. Given that the results of the log-linear model are very similar to the linear model ones, the remaining of this section alternatively considers absolute or logarithmic prices according to the immediacy of the coefficients' interpretation.[21]

Interpretation of individual weather forecasts, when the summary proxy is one of the eight icons described in Table 7, can be problematic. As explained above, we then simplified the analysis by clustering the eight codes into simple binary variables, *No_rain* and *Sun*. In Model (1.5) of Table 1, in which *No_rain* was included, the main result is confirmed: prices are on average 3.5% higher when forecasts exclude rain. The coefficient is very similar also in Model (1.6), in which *Sun* was inserted, suggesting that the forecast of a sunny day increased the price by 3.6%.

A similar robustness test was undertaken in Models (1.7) and (1.8), where, respectively, the forecast maximum and average daily temperature were included in the model as proxies for *WF*. All the estimated coefficients for the variables included in the regression and their significance are very similar to the log-linear model in (1.5): every Celsius degree more in the forecast of maximum temperature is associated with an increase of 1.76% in the average daily price, *ceteris paribus* (see Model 1.7). Similarly, every extra Celsius degree in the forecast mean temperature was associated with an increase of 1.60% in the average daily price (see Model 1.8).

Finally, Models (1.9) and (1.10) in Table 1 are run on an extended dataset, where all the possible rooms (double, triple, quadruple, etc.), party groups (two adults with and without two children), and length of stay (weekends and one-week holidays) are considered, with robust errors clustered by hotel. To simplify the reading, weather forecasts are proxied by the binary variable *No_rain* (results are robust to the alternative inclusion of *WF* or *Sun* in the regression). In Model (1.9), we only consider weekends of party groups with or without children and, consequently, a wider range of rooms, including double, triple, and quadruple rooms, together with entire apartments and villas (about 230,000 observations). The estimated coefficient of *No_rain* is very similar to the one of Model (1.5), hence reinforcing Hypothesis 1. In Model (1.10), we include double rooms and parties of two adults only (as in Models 1.1 to 1.8), but both weekends and one-week holidays are considered. Although the coefficient of *No_rain* in (1.10) is still positive and significant, its value is lower (0.0123), suggesting a weakening of the impact. This is somehow expected, especially if we consider that in a sea & sun destination in Southern Europe, bad weather usually lasts for one or, in the worst-case scenario, two or three days. Hence, it is unlikely that a bad weather

[21] All findings are available upon request and results that are not robust with the main findings are always reported in the paper.

forecast for the check-in day would affect the decision to travel to the destination for a whole week.[22]

### 4.2 Testing Hypotheses 2 and 3: the Role of Signal Accuracy and Ex-ante Uncertainty

In Table 2, we report the results for testing Hypothesis 2 about the role of signal accuracy, proxied by the time distance between the check-in day and the posting day. Models (2.1) and (2.2) can be compared to Model (1.5), where the logarithmic daily price of one room for two adults for a weekend stay is regressed over *No_rain* and the standard set of control variables outlined in Eq. (20). In Model (2.1), only the last three days of the booking period were considered, whereas, in Model (2.2), we included the complementary period, i.e., from 4 up to 15 days in advance. The same comparison was carried out in (2.3) and (2.4), with the price in levels as the dependent variable.

Results are consistent with Hypothesis 2: the effect of weather forecasts is stronger the shorter the time lag, as the accuracy of the information embodied in the forecasts improves; accordingly, the coefficient of *No_rain* estimated in (2.1) is larger than the one estimated in (2.2), and the coefficient of *No_rain* estimated in (2.3) is larger than the one estimated in (2.4), which becomes statistically not significant. Such results were confirmed in regressions (2.5) to (2.8), run on the extended dataset with different party groups (adults with or without children) and different room sizes (double, triple, quadruple, etc.): the coefficient of *No_rain* estimated in the log-linear regression (2.5) is larger than the one estimated in (2.6), whereas the coefficient estimated in the linear regression (2.7) is larger than the one estimated in (2.8), which becomes not significant.

Finally, in Models (2.9) and (2.10), we run models (2.7) and (2.8) but replace the binary variable *No_rain* with the weather forecast codes described in Table 3. Although not all the forecast coefficients are significant, it is worthwhile to highlight that the strongest impact of weather forecasts in the last three days before check-in (Model (2.9)) comes from forecasts associated with consistent bad weather (cloudy, overcast), which are likely to continue for the whole weekend. On the contrary, forecasts of unstable bad weather (thunderstorms), likely to last 2–3 h, only partially ruin a hypothetical weekend.[23]

Regarding testing Hypothesis 3, about the role of ex-ante uncertainty proxied by the historical weather conditions in different summer season months, we run the hedonic

[22] In our sample, most of the hotels indeed used some form of dynamic pricing, somehow different from what found by Melis and Piga (2017). However, there were 194,956 observations (18% of the observations with a valid price) where the price of a given room in a given hotel for the same check-in date never changed in the advance booking period. When this group of observations were excluded from the regression, the coefficient of *No_rain* became larger (0.04496, significant at the 1% level) than the coefficient in the equivalent model (1.5), where the estimate was 0.0349, reinforcing the support of the rationale behind the model. Unsurprisingly, the coefficient of *No_rain* was instead insignificant (and equal to -0.0009) when the regression was run on the subsample of observations where price discrimination was not used.

[23] We also observe that some of the controls' coefficients differ between "even" and "odd" numbered Models of Table 2: in the regressions run on prices posted in the last three days before the check-in date (odd Models), the set of *Available rooms* dummies is seldom significant; moreover, the positive sign of the coefficient of *Lead time* suggests the implementation of a sort of last minute pricing; finally, the most important factor affecting the posted price is always *Special offer*, i.e., the price posted as a special offer.

**Table 2** Impact of weather forecasts on prices: the role of accuracy

| | (2.1) lnP, double room, two adults, τ < 4 | (2.2) lnP, double room, two adults, τ > 3 | (2.3) P, double room, two adults, τ < 4 | (2.4) P, double room, two adults, τ > 3 | (2.5) lnP, any room, any party, τ < 4 |
|---|---|---|---|---|---|
| No_rain | 0.0391**[2.36] | 0.0182***[3.86] | 14.15***[2.81] | − 0.149 [− 0.22] | 0.0350***[5.39] |
| WF 2 | | | | | |
| WF 3 | | | | | |
| WF 4 | | | | | |
| WF 5 | | | | | |
| WF 7 | | | | | |
| WF 8 | | | | | |
| Free cancellation | − 0.0313 [− 1.06] | 0.0361*[1.85] | − 3.492 [− 0.72] | 3.218 [0.95] | − 0.000969 [− 0.12] |
| Lead time | 0.0146***[2.87] | − 0.0102***[− 8.64] | 0.258 [0.33] | − 1.398***[− 5.01] | 0.0154***[8.20] |
| Special offer | − 0.202***[− 7.48] | − 0.192***[− 10.94] | − 20.64***[− 5.15] | − 19.13***[− 6.81] | − 0.216***[− 45.21] |
| Available rooms (1) | 0.117**[2.49] | 0.0774**[2.18] | 3.858 [0.53] | 6.008 [1.36] | 0.0984***[9.67] |
| Available rooms (2) | 0.0686 [1.56] | 0.0872**[2.49] | − 1.521 [− 0.24] | 7.088 [1.55] | 0.0612***[6.11] |
| Available rooms (3) | 0.0343 [0.73] | 0.0400 [1.15] | − 5.134 [− 0.70] | 2.312 [0.54] | 0.0506***[4.70] |
| Available rooms (4) | 0.103*[1.78] | 0.0333 [0.91] | 3.575 [0.51] | 0.922 [0.19] | 0.0739***[6.65] |
| Available rooms (5) | 0.0124 [0.25] | 0.0482 [1.42] | − 2.215 [− 0.32] | 1.893 [0.42] | − 0.00635 [− 0.53] |
| Kids | | | | | 0.106***[13.98] |
| Room type * Hotel | YES | YES | YES | YES | |
| Hotel | | | | | YES |
| Room type | | | | | YES |
| Constant | 4.615***[55.86] | 3.918***[62.35] | 106.4***[9.76] | 68.45***[8.70] | 4.049***[127.44] |
| *N* | 19,793 | 72,344 | 19,793 | 72,344 | 49,599 |
| adj. $R^2$ | 0.728 | 0.649 | 0.606 | 0.538 | 0.712 |

**Table 2** (continued)

| | (2.6)<br>lnP, any room, any party, τ > 3 | (2.7)<br>P, any room, any party, τ < 4 | (2.8)<br>P, any room, any party, τ > 3 | (2.9)<br>P, any room, any party, τ < 4 | (2.10)<br>P, any room, any party, τ > 3 |
|---|---|---|---|---|---|
| No_rain | 0.0217***[10.10] | 11.90***[6.49] | − 0.188 [− 0.49] | | |
| WF 2 | | | | 2.107 [1.34] | − 5.114***[− 6.51] |
| WF 3 | | | | 0.285 [0.21] | − 5.251***[− 7.86] |
| WF 4 | | | | − 9.935***[− 4.93] | − 7.240***[− 9.53] |
| WF 5 | | | | − 14.87***[− 5.36] | − 1.255 [− 1.05] |
| WF 7 | | | | | − 1.443*[− 1.72] |
| WF 8 | | | | − 7.639***[− 3.26] | − 7.005***[− 3.47] |
| Free cancellation | 0.0279***[9.81] | − 1.182 [− 0.95] | 3.080***[6.17] | − 1.017 [− 0.82] | 3.435***[6.96] |
| Lead time | − 0.00852***[− 26.90] | 0.502 [1.45] | − 1.123***[− 18.40] | 1.165***[2.70] | − 1.047***[− 16.80] |
| Special offer | − 0.199***[− 75.50] | − 23.12***[− 28.72] | − 19.54***[− 57.08] | − 23.03***[− 27.84] | − 20.41***[− 56.19] |
| Available rooms (1) | 0.125***[23.42] | 4.085***[2.83] | 12.57***[18.69] | 4.142***[2.87] | 12.61***[18.77] |
| Available rooms (2) | 0.114***[21.56] | − 2.076 [− 1.48] | 9.837***[14.87] | − 2.014 [− 1.43] | 9.855***[14.91] |
| Available rooms (3) | 0.0887***[16.30] | − 1.051 [− 0.64] | 7.472***[10.94] | − 1.023 [− 0.63] | 7.557***[11.07] |
| Available rooms (4) | 0.0884***[15.31] | 1.775 [1.18] | 6.886***[10.27] | 1.801 [1.20] | 6.925***[10.35] |
| Available rooms (5) | 0.0557***[9.09] | − 7.213***[− 4.32] | 2.708***[3.73] | − 7.255***[− 4.35] | 2.734***[3.77] |
| Kids | 0.0716***[20.27] | 20.25***[9.69] | 11.43***[16.56] | 20.24***[9.68] | 11.14***[16.19] |
| Room type * Hotel | | | | | |
| Hotel | YES | YES | YES | YES | YES |
| Room type | YES | YES | YES | YES | YES |
| Constant | 3.660***[71.94] | 30.42***[5.92] | 29.96***[6.99] | 40.46***[8.30] | 33.76***[7.83] |

**Table 2** (continued)

| | (2.6) | (2.7) | (2.8) | (2.9) | (2.10) |
|---|---|---|---|---|---|
| | lnP, any room, any party, $\tau > 3$ | P, any room, any party, $\tau < 4$ | P, any room, any party, $\tau > 3$ | P, any room, any party, $\tau < 4$ | P, any room, any party, $\tau > 3$ |
| *N* | 180,493 | 49,599 | 180,493 | 49,599 | 180,493 |
| adj. $R^2$ | 0.633 | 0.607 | 0.539 | 0.608 | 0.539 |

t-statistics in brackets; $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. In all specifications, errors are clustered by hotel. The dependent variable is price *P* in models (2.3), (2.4), (2.7–2.10) and the logarithm of price *lnP* in the other models. Models (2.1) to (2.4) only include observations related to a double room for two adults; models (2.5) to (2.10) include observations related to any combination of rooms for a party group of two adults and two kids. All models only include observations related to a weekend stay of two nights (from Friday to Sunday). Models (2.1), (2.3), (2.5), (2.7) and (2.9) only include observations for *Lead time* < 4 (i.e., prices posted in the last three days of the advance booking before the check-in date). Models (2.2), (2.4), (2.6), (2.8) and (2.10) only include observations for *Lead time* > 3 (i.e., prices posted from 15 to 4 days in advance before the check-in date). Controls included in every model*: Check-in dates, Board type*

**Table 3** Impact of weather forecasts on prices: the role of uncertainty and hotel category

| | (3.1) lnP, June and Sept | (3.2) lnP, July and Aug | (3.3) P, June and Sept | (3.4) P, July and Aug | (3.5) lnP, 1–3 stars | (3.6) lnP, 4–5 stars | (3.7) P, 1–3 stars | (3.8) P, 4–5 stars |
|---|---|---|---|---|---|---|---|---|
| No_rain | 0.057***[8.69] | 0.003 [0.44] | 3.641***[5.58] | 2.343 [1.35] | 0.033***[5.62] | 0.041***[4.14] | 3.108***[3.01] | 3.739*[1.82] |
| Free cancellation | 0.040***[2.83] | 0.001 [0.06] | 4.848**[2.58] | − 1.521 [− 0.29] | 0.026**[2.06] | 0.061 [1.43] | 0.768 [0.40] | 14.09 [1.47] |
| Lead time | − 0.008***[− 5.56] | − 0.006***[− 3.54] | − 0.631***[− 3.43] | − 1.627***[− 3.20] | − 0.007***[− 5.28] | − 0.009***[− 3.42] | − 0.839***[− 3.83] | − 1.769**[− 2.53] |
| Special offer | − 0.137***[− 7.61] | − 0.277***[− 8.31] | − 16.61***[− 8.17] | − 25.56***[− 5.84] | − 0.182***[− 9.08] | − 0.203***[− 6.54] | − 17.27***[− 5.91] | − 22.86***[− 4.11] |
| Available rooms (1) | 0.113**[2.58] | 0.065**[2.03] | 8.351*[1.87] | 12.82**[2.16] | 0.107**[2.29] | 0.080*[1.83] | 8.761 [1.52] | 8.422 [1.09] |
| Available rooms (2) | 0.109**[2.50] | 0.061*[1.77] | 7.482*[1.68] | 12.24**[1.97] | 0.106**[2.34] | 0.077*[1.68] | 7.266 [1.28] | 7.620 [0.97] |
| Available rooms (3) | 0.091**[2.05] | 0.011 [0.36] | 9.204*[1.89] | 1.233 [0.23] | 0.067 [1.44] | 0.031 [0.77] | 5.450 [0.98] | − 0.186 [− 0.03] |
| Available rooms (4) | 0.048 [0.98] | 0.061 [1.46] | 3.114 [0.73] | 4.312 [0.54] | 0.088*[1.81] | − 0.025 [− 0.56] | 7.459 [1.35] | − 7.240 [− 0.97] |
| Available rooms (5) | 0.053 [1.20] | 0.028 [0.83] | 3.339 [0.77] | 4.768 [0.86] | 0.078*[1.76] | 0.002 [0.04] | 6.800 [1.46] | − 5.450 [− 0.69] |
| Constant | 3.907***[60.09] | 4.783***[57.00] | 61.59***[9.67] | 128.8***[8.85] | 3.870***[48.83] | 3.649***[31.99] | 62.96***[6.44] | 39.25**[2.42] |
| *N* | 48,999 | 43,138 | 48,999 | 43,138 | 69,917 | 22,220 | 69,917 | 22,220 |
| adj. R2 | 0.584 | 0.667 | 0.532 | 0.598 | 0.614 | 0.656 | 0.505 | 0.555 |

t-statistics in brackets; $*p < 0.10$; $**p < 0.05$; $***p < 0.01$. In all specifications, errors are clustered by hotel. The dependent variable is price *P* in models (3.3), (3.4), (3.7), (3.8) and the logarithm of price *lnP* in the other models. All models include observations only about a double room for two adults and a weekend stay of two nights (from Friday to Sunday). Models (3.1) and (3.3) only include observations of June and September; Models (3.2) and (3.4) only include observations of July and August. Models (3.5) and (3.7) only include observations of 1, 2, and 3-star hotels; Models (3.6) and (3.8) only include observations of 4-star hotels. Controls included in every model: *Room type * Hotel, Check-in dates, Board type* model separately for peak and off-peak months, as reported in Table 3 (Models 3.1 to 3.4). June and September (Models (3.1) and (3.3)) are the summer months with the highest level of weather uncertainty according to historical data for Rimini. In contrast, July and August are characterized by the lowest weather uncertainty (Models (3.2) and (3.4)). Results are reported in Table 3, with the daily price expressed in logarithms (Models (3.1) and (3.2)) and in levels (Models (3.3) and (3.4)). For simplicity, in the models in Table 3, the weather forecast is measured by including the binary variable *No_rain*.

In line with Hypothesis 3, we find that the estimated coefficients of *No_rain* are higher (and significant) in the period of high weather uncertainty in both the linear and log-linear regressions (one should compare the estimated coefficient of *No_rain* in 3.1 and 3.3, which are higher than the one estimated respectively in 3.2 and 3.4).[24] However, the coefficients of *No_rain* in the season with low weather uncertainty (July and August) are not significant. This result arguably stems from the fact that in the period of low weather uncertainty, the frequency of *No_rain* is particularly low. When the extended dataset is used, including all the rooms and party groups (rather than only parties of two adults searching for one double room as in Models 3.1 to 3.4), results are indeed supportive of Hypothesis 3: in the log-linear regression, the coefficient of *No_rain* is larger in June and September (0.055, significant at the 1%) than in July and August (0.009, this time significant at the 1%).[25]

### 4.3 Testing Hypothesis 4: Price Reactions by Hotel Category and the Role of Managerial Sophistication

We finally test Hypothesis 4, exploring the possibility that firms may respond differently to weather forecasts according to their degree of managerial sophistication. For this purpose, in Table 3 (Models 3.5 to 3.8), we estimate the hedonic pricing model separately for upper-scale hotels (4- and 5-star hotels, Models 3.6 and 3.8) and low- and mid-scale hotels (1-, 2- and 3-star hotels, Models 3.5 and 3.7). Our results show that the response of prices to weather forecasts is larger for upper-scale than for low/mid-scale hotels, both when the price is in levels (the coefficient of *No_rain* is larger in Model 3.8 than in 3.7) and in logarithms (the coefficient of *No_rain* is larger in Model 3.6 than in 3.5). These results are robust to using the extended dataset, where all the rooms and party groups are considered. Hypothesis 4 is thus confirmed.

[24] Additional support to Hypothesis 3 stems from the fact that when the baseline Model in (1.5) is run only on prices posted with the option of *Free cancellation*, for which the value of information about future weather is arguably less important, the coefficient of *No_rain* is 0.0166 and significant at the 5% level only. Alternatively, if the model is run only on prices posted without the option of *Free cancellation*, for which information about future weather is instead more important, the coefficient of *No_rain* is 0.0418 and significant at the 1% level.

[25] Full results are available upon request.

## 5 Conclusions

The key role played by public information in market economies is self-evident. Alas, empirical investigation on how prices are affected is hindered by the coexistence with private information, ambiguity on how information might impact the economic variables of interest, and endogeneity issues. This article contributes to the ongoing debate on the role of information in price setting by analyzing the impact of weather forecasts (as an example of public and symmetric information) on prices in the hotel sector of a leisure destination. In this market, weather conditions (which are clearly exogenous) directly affect demand.

To do so, we first develop a theoretical model where forecasts are common knowledge and can be observed by both accommodation service providers and consumers. The former are sophisticated enough to make their prices contingent on weather forecasts. As the quality of the leisure experience is affected by weather conditions, weather forecasts (as a signal for expected quality) affect the willingness to pay of customers and hence equilibrium prices: a forecast of good weather increases the expected quality of the experience and drives the supply to instantaneously adjust the price, the effect being stronger the higher the level of accuracy of the forecast and the larger the degree of *ex-ante* uncertainty in weather conditions. By comparing the results under the assumption of flexible prices with the case in which firms are constrained to fix a single price, we show that the additional profit from price flexibility, and so the return to the investment in pricing capability, is increasing in consumers' willingness to pay.

Predictions of the theoretical analysis are then estimated through an augmented hedonic model where dynamic characteristics (typical of advanced booking strategies) are included with information about weather forecasts and other control variables. The model is tested on big data collected in the summer season of a typical sea & sun destination (Rimini, Italy), where most of the leisure activities are carried out *open-air*, hence being heavily dependent on weather conditions. Results robustly support the theory and show that pricing does react to available weather information, an essential and independent determinant of the price: *ceteris paribus*, the worse the weather forecast, the lower the price, in line with Hypothesis 1. As predicted by the flexible price model, the impact is larger the higher the forecast's level of accuracy, i.e., when the forecast day is closer to the arrival date, and in those months in which weather is much uncertain, i.e., the higher the *ex-ante* level of uncertainty in weather, thus supporting Hypotheses 2 and 3, respectively. In an additional exercise, we estimate the hedonic pricing model separately for upper-scale hotels (4- and 5-star hotels) and low- and mid-scale hotels (1-, 2- and 3-star hotels). We find that the response of prices to weather forecasts is larger for upper-scale hotels than for low- and mid-scale hotels, a result we link to the higher incentives to invest in managerial pricing competencies that characterize the former compared to the latter, which confirms Hypothesis 4. Overall, our results support the traditional view of pricing reacting significantly to public (weather) information and, on the contrary, they are not consistent with the literature on "behavioral firms".

Despite the richness of our data set, which allows us to provide some additional understanding of tourism-relevant behavior (Xu et al. 2020), our work has a few limitations, which constitute the main avenues for future research on the topic. For instance, the theoretical approach could be extended to a more general scenario in which good and bad weather signals have different degrees of accuracy and are biased (Silver, 2012; Raymond and Taylor, 2020). Also, including a behavioral dimension on the consumer side seems a promising direction, as there is evidence that individuals have problems interpreting weather forecast probability correctly (Gigerenzer et al. 2005; Juanchich and Sirota, 2016).

On the empirical side, the first issue concerns replicability, as our results are based on one single destination and one single summer. More in general, different destinations might respond to weather conditions differently. We expect that the relevance of weather would differ according to the tourism type: cultural tourism is probably less sensitive to weather than leisure tourism (in terms of model set-up, $\alpha$ would be higher for cultural tourists). Therefore, the price elasticity to weather forecasts would be lower in cultural destinations. Moreover, the computation of the sector's net loss in terms of profits and welfare due to bad weather and bad forecasts needs access to microdata of hotels, something that is worthy of being investigated given the policy implications at the destination level. Finally, in an era of climate alterations, weather conditions change, thus implying more variability within the season and a higher frequency of extreme events (Dell et al. 2014). These changes are likely to affect both the accuracy of weather forecasts and the willingness to pay of customers for more risky holiday breaks. Hence, a future extension of the empirical analysis will have to monitor changes in consumer behavior and innovation in hotels' implementation of pricing strategies.

The extension of the current study to more recent years, especially post-pandemic, characterized by a rise of the sharing economy also in the tourism sector (Vila-Lopez and Küster-Boluda 2021) is finally important. Platforms such as Airbnb are now frequently visited when choosing accommodation, representing a relevant source of competition to the hotel sector. For instance, there is ample evidence showing that during the pandemic, to avoid as much as possible physical contact and the sharing of shared spaces, entire flats on Airbnb were much preferred over shared flats or hotel rooms (Bresciani et al. 2021). Future research would clarify if our findings can be extended to these other segments of the accommodation sector.

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## Declarations

**Conflict of interest** None.

# Appendix 1: Proofs

## A.1 Proof of Proposition 2

The impact of $q$ on prices is inversely related to the impact of $q$ on $\beta_{\text{“}g\text{”}}$ and $\beta_{\text{“}b\text{”}}$. Straightforward derivations yield:

$$\frac{d\beta_{\text{“}g\text{”}}}{dq} = \frac{(2r-1)[rq+\alpha(1-r)(1-q)]-[r-\alpha(1-r)][rq+(1-r)(1-q)]}{[rq+\alpha(1-r)(1-q)]^2} \tag{21}$$

The denominator in (21) is positive. The numerator is 0 for $\alpha = 1$, and is increasing in $\alpha$. Therefore $\frac{d\beta_{\text{“}g\text{”}}}{dq} \leq 0$, i.e., $p^*_{\text{“}g\text{”}}$ is increasing in $q$.

Similarly,

$$\frac{d\beta_{\text{“}b\text{”}}}{dq} = \frac{-(2r-1)[r(1-q)+\alpha(1-r)q]+[r-\alpha(1-r)][r(1-q)+(1-r)q]}{[r(1-q)+\alpha(1-r)q]^2} \tag{22}$$

The denominator in (22) is positive. The numerator is 0 for $\alpha = 1$, and is decreasing in $\alpha$. Therefore $\frac{d\beta_{\text{“}g\text{”}}}{dq} \geq 0$, i.e., $p^*_{\text{“}g\text{”}}$ is decreasing in $q$. It follows that $\Delta p^*$ and $\%\Delta p^*$ are both increasing in $q$.

## A.2 Proof of Proposition 3

By deriving $\Delta p^*$ with respect to $r$, after some manipulations one obtains:

$$\frac{d\Delta p^*}{dr} = \frac{\overline{\theta}(2q-1)(1-\alpha)}{2}\,\frac{(1-2r)[rq+\alpha(1-r)(1-q)][r(1-q)+\alpha(1-r)q]-r(1-r)(2r-1)(2q-1)}{[rq+\alpha(1-r)(1-q)]^2[r(1-q)+\alpha(1-r)q]^2} < 0 \tag{23}$$

which is negative as $r \geq \frac{1}{2}$ and $q \geq \frac{1}{2}$.

Similarly, deriving $\%\Delta p^*$ with respect to $r$, yields, after lengthy manipulations:

$$\frac{d\%\Delta p^*}{dr} = -\frac{(2q-1)^2(1-\alpha)q(1-q)\left[r^2-\alpha(1-r)^2)\right]}{[rq+(1-r)(1-q)]^2[r(1-q)+\alpha(1-r)q]^2} < 0 \tag{24}$$

which is negative as $r \geq \frac{1}{2}$.

## Appendix 2: Technical issues related to the construction of the data set and descriptive statistics

*Party Groups* As Rimini is a popular destination for both couples and families, searches for party groups of two adults only and two adults with two children were collected each day for each type of stay (weekend and one-week holiday).

*Coding of Rooms* The scraper searched for all the types of rooms on offer. This was necessary to avoid bias in the estimation due to the alternative availability or unavailability of certain rooms along the lead booking period and the season. Consequently, to track the correct price changes over time, we had to control each hotel's different room types. Hence, each room was manually recoded according to two dimensions: size and category. In the final dataset, the room code was composed of two digits. The first digit indicates the size of the room: 1* indicates a single room, 2* a double room, 3* a triple room, 4* a quadruple room, 5* a twin double room; 6* an apartment; 7* a suite, 8* a beach package, 9* a bed in a dormitory. The second digit indicates the category: *0 means that no further information about the type of room was provided, *1 indicates that the room was economy / basic / budget, *2 that the room was standard / classic / business / comfort, *3 that the room was standard / classic / business / comfort but with view / balcony / access spa / access beach, *4 indicates that the room was superior / deluxe / executive / premium / king, *5 that the room was superior / deluxe / executive / premium / king but with view / balcony / access spa / access beach. For example, a superior double room with a balcony was coded as 25, and the same code defined a deluxe double room with a sea view. This coding allowed us to exploit as much information as possible by normalizing the room type and comparing prices offered by different hotels, which often name rooms differently.

*Data cleaning* After data cleaning and checking (some observations were deleted because of errors in the scraping or missing relevant information), the dataset of almost 1.1 million observations and 23 variables related to 879 hotels was reduced to about 833,000 observations and 17 relevant variables. In fact, some data were lost because of the frequent changes in the structure of the booking platform, which implied the re-programming of the scraper, an action that in some cases took more than one day (Tables 4, 5, 6, 7, 8).

**Table 4** Price and booking variables

| Variable name | Description | Nr. observations | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|
| Price | Total price of booking | 833,543 | 486.56 | 512.49 | 0 | 14,000 |
| P | Daily price of booking | 833,543 | 103.96 | 87.04 | 0 | 2800 |
| Hotel | Hotel code | 996,919 | 460.87 | 243.29 | 1 | 879 |
| Special offer | Dummy: is it a special offer? | 996,920 | .256 | .436 | 0 | 1 |
| Score* | Hotel's rating | 890,217 | 7.79 | .923 | 3.5 | 9.8 |
| Stars | Category of the hotel | 870,935 | 2.97 | .680 | 1 | 5 |
| Available rooms | Nr. of available rooms on the platform | 784,451 | 1.76 | 1.07 | 1 | 5 |
| Adults | Nr. of adults to accommodate | 990,160 | 2 | 0 | 2 | 2 |
| Kids | Nr. of children to accommodate | 990,160 | .276 | .690 | 0 | 2 |
| Check-in | Date of check-in | 998,562 | | | 29 May | 25 September |
| Check-out | Date of check out | 996,920 | | | 31 May | 27 September |
| LOS | Length of stay | 996,920 | 4.65 | 2.48 | 2 | 7 |
| Free cancellation | Dummy: is there free cancellation? | 996,920 | .354 | .478 | 0 | 1 |
| Board type** | Type of board | 996,920 | 1.03 | .211 | 0 | 4 |
| Lag time | Diff. between check-in and search dates | 996,920 | 6.81 | 5.40 | 0 | 15 |
| Room type*** | Type of room | 747,025 | 32.09 | 18.97 | 10 | 90 |

*Categorical variable coding the overall evaluation of the hotel on Booking.com, originally expressed in words (excellent, good, etc.)
**Categorical variable coding the type of board provided in the offer: 0 = breakfast not included 1 = bed & breakfast; 2 = half-board; 3 = half-board with lunch; 4 = full-board
***Categorical variable coding the type of room in terms of capacity (e.g., double room, triple room, etc.) and quality (e.g., Superior room, room with sea view, etc.)

**Table 5** Popularity and ratings of the most important weather forecast apps used in Italy

| Name | Ilmeteo.it | Meteo.it | 3Bmeteo | MeteoAM |
|---|---|---|---|---|
| Nr. of downloads (Play Store) | > 10 million | > 5 million | > 1 million | > 0.5 million |
| Average rating | 4.3 | 4.0 | 4.3 | 4.1 |
| Number of ratings | 460,187 | 101,475 | 141,262 | 5074 |
| Share of 1/5 votes | 3.61% | 8.91% | 2.27% | 6.90% |
| Share of 2/5 votes | 2.34% | 4.72% | 1.64% | 5.66% |
| Share of 3/5 votes | 7.93% | 12.56% | 6.87% | 11.17% |
| Share of 4/5 votes | 33.63% | 32.13% | 39.53% | 27.36% |
| Share of 5/5 votes | 52,59% | 41.68% | 49.70% | 48.92% |

Data were updated on 10 April 2018

**Table 6** Summary statistics for IlMeteo weather forecasts

| Variable | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Dump time | 1942 | | | 13 May | 27 September |
| Forecast date | 1942 | | | 15 May | 30 September |
| Min temp | 1942 | 21.03 | 3.28 | 11 | 27 |
| Average temp | 1942 | 24.94 | 2.68 | 13.5 | 31.5 |
| Max temp | 1942 | 27.72 | 3.64 | 15 | 37 |
| Weather Forecast code* | 1942 | 5.76 | 3.06 | 1 | 8 |
| Lag time** | 1942 | 6.91 | 4.32 | 0 | 15 |

*Codes relative to the summary weather conditions, as described in Table 3
**Difference (in days) between the day when the forecast was produced and the forecast day

**Table 7** Weather forecasts produced by IlMeteo, Rimini

| Forecast icon (and code) | Frequency | Share | Cumulative share |
|---|---|---|---|
| Hot and sunny (WF 1) | 279 | 14.37 | 14.37 |
| Blue sky (WF 2) | 185 | 9.47 | 23.84 |
| Overcast / unstable (WF 3) | 544 | 28.01 | 51.91 |
| Downpour / clear up (WF 4) | 397 | 20.44 | 72.35 |
| Cloudy (WF 5) | 119 | 6.12 | 78.48 |
| Misty rain (WF 6) | 14 | 0.72 | 79.20 |
| Rain (WF 7) | 284 | 14.62 | 93.82 |
| Shower / thunderstorm (WF 8) | 120 | 6.18 | 100.00 |
| Total | 1942 | 100.00 | 100.00 |

**Table 8** Summary statistics for real weather, Rimini

| Variable | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Daily rain (mm) | 138 | 2.53 | 7.99 | 0 | 48.6 |
| Daily pressure (bar) | 138 | 1013.22 | 4.18 | 1004.35 | 1023.63 |
| Daily max temp. (C°) | 138 | 27.03 | 4.21 | 15 | 36.3 |
| Daily aver. temp. (C°) | 138 | 23.42 | 3.82 | 13.18 | 30.53 |
| Daily min temp. (C°) | 138 | 19.26 | 3.67 | 10.9 | 26.1 |
| Daily max hum. (%) | 138 | 79.11 | 9.90 | 52 | 99 |
| Daily mean hum. (%) | 138 | 61.26 | 9.51 | 36.67 | 90.96 |
| Daily min hum. (%) | 138 | 41.35 | 10.55 | 19 | 76 |
| Daily wind direction* | 138 | 4.14 | 2.05 | 1 | 8 |
| Daily wind speed (m/s) | 138 | 2.17 | .58 | 1.4 | 5.08 |

*Coded clockwise from 1 (northern) to 8 (north-western)

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