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Hotels, prices and risk premium in exceptional times: The case of Milan hotels during the first COVID-19 outbreak

Anastasia Arabadzhyan [a], Paolo Figini [b,*,1], Lorenzo Zirulia [c,2]

[a] Centre for Health Economics, University of York, Heslington, York YO10 5DD, UK
[b] Department of Economics and CAST, Centre for Advanced Studies in Tourism, University of Bologna, Piazza Scaravilli 2, 40126 Bologna, Italy
[c] Department of Economics, University of Bologna, Piazza Scaravilli 2, 40126 Bologna, Italy

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ABSTRACT

The COVID-19 outbreak affects hotels by changing demand and supply. We investigate the case of Milan, the outbreak epicentre in Europe, by studying the hotels' reaction before, during, and after the lockdown. We monitor room offers and prices posted on Booking.com in January–September 2020. Findings suggest that: i) the reaction at the beginning of the pandemic was a fall in prices; ii) the number of active hotels dropped with the lockdown, while prices stabilised, a fact that we attribute to fairness considerations; iii) hotels managed uncertainty by increasing the free cancellation options and the risk premium, especially for short-term leads; iv) news and expectations on the pandemic, and the introduction of travel limitations, were essential drivers of managerial decisions.

1. Introduction and positioning

The COVID-19 pandemic led the world economy into the most severe recession since World War II, with global GDP falling by 4.3% in 2020 (World Bank, 2021). Hospitality and tourism were among the most affected industries, and the pandemic caused a drop of 74% in international tourism arrivals in 2020 compared to 2019 (UNWTO, 2021).

In the hospitality sector, the COVID-19 outbreak impacted the market by simultaneously changing conditions in demand and supply, similar to what happened during other health crises such as SARS (Chen, Jang, & Kim, 2007; Chien & Law, 2003). Travel bans (which in most cases also limited within-country mobility) were introduced by public authorities during the lockdown, affecting the demand. In addition, in the post-lockdown phase, the difficulty of travelling under strict safety measures, jointly with the substantial uncertainty related to how restrictions would be lifted, and the tighter budget constraint triggered by the economic recession, shifted the demand curve down. On the supply side, the introduction of health and safety protocols and regulations, jointly with other limitations involving daily activities (from buffet breakfast to the use of common areas), generally increased production costs.

In an industry strongly characterised by advance booking (Abrate, Nicolau, & Viglia, 2019), the reaction to shocks is mainly driven by information clues about the future and agents' expectations. With the COVID-19 outbreak, customers and tourism operators learned that leisure activities and travelling were increasingly becoming more difficult. Information on the pandemic's diffusion, the new rules imposed by governments to consumption and production activities, and the limitations in social interaction were embodied into the pricing structure and supply available at different lead times and dates of posting. This is relevant for the whole pandemic period: with the outburst of the disease, when news impacted agents' behaviour while limitations were progressively imposed; during the lockdown, when information about future reopening was circulated by public authorities, with agents thereby adjusting expectations; after the lockdown, when demand started to revive, with hotels changing their offer to the progressive lifting of rules and protocols.

In this context of exceptional turbulence, this paper conducted an exploratory analysis of hotels' strategies during the first wave of the pandemic, using Milan (Italy) as an enlightening case study. Milan, the administrative capital of Lombardy and the engine of the Italian economy, was arguably the epicentre of the pandemic outbreak in Europe in Spring

* Corresponding author.
E-mail addresses: anastasia.arabadzhyan@york.ac.uk (A. Arabadzhyan), paolo.figini@unibo.it (P. Figini), lorenzo.zirulia@unibo.it (L. Zirulia).

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[2] Present address: Department of Economics, Management and Quantitative Methods, University of Milan, via Conservatorio 7, 20,122, Milan. *E*-mail: lorenzo.zirulia@unimi.it.

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2020. On September 21, 2020, the last day of our sample, 35% (104,848) of the 299,506 COVID-19 official cases detected in Italy were in Lombardy, with 16,923 deaths (47.4% of the total 35,724 deaths recorded in Italy at the time).

We investigated the reaction of hotels to changing market and regulatory conditions by looking at the dynamics of room availability and prices posted on Booking.com, an important booking engine, from January 1 to September 21, 2020.[3] This way, we covered the whole lockdown period in Lombardy and Italy, up to the beginning of the second wave, which started in October 2020. Specifically, we collected the offers posted by 104 4-star hotels in the city of Milan for different lead times and different booking conditions, mainly analysing the evolution of free cancellation (FC) and non-refundable (NR) fares over time.

Our main findings can be summarised as follows: one, the immediate reaction to the COVID-19 outbreak was a drop in prices in the period just before the lockdown. Two, during the lockdown, the adjustment in the number of hotels that stayed on the market was the most significant evidence. At the same time, prices exhibited stability which, we argue, is motivated by fairness considerations. Three, hotels managed uncertainty by increasing the offer of free cancellation fares and through (temporary) surges in the risk premium, especially for short-term leads. Finally, news and expectations about the pandemic and the introduction of new regulations were relevant drivers of managerial decisions. Findings also suggest that throughout the different phases of the pandemic, the sector was excessively optimistic on future demand and the possibility to return to normality quickly.

Our work analysed hotels' dynamic pricing and managerial decisions in exceptional times. Revenue management is a strategic tool extensively investigated by the literature (Abrate & Viglia, 2016; Blengini & Heo, 2020; Guizzardi, Pons, & Ranieri, 2017; Melis & Piga, 2017; Mitra, 2020), and a few papers have also analysed pricing strategies in times of crises (Caudillo-Fuentes & Li, 2010; Gehrels & Blanar, 2013). In such conditions, hotels can react to abrupt changes in market conditions with different managerial actions: they can cease operations, change their pricing strategy, or use a diverse menu of fare options. Specifically, when adverse demand shocks are severe, as during the pandemic, closing operations may be the optimal choice to reduce losses, a decision that in "normal times" is only linked to seasonality issues. Moreover, while cancellation policies have the primary role of managing customer idiosyncratic risk (Chen, 2016; Chen & Xie, 2013), our paper provides evidence of hotels fine-tuning this option when the systemic market risk changes. Overall, we observed a full range of reactions, both cross-section (some hotels closed, some others stayed open) and over time (some hotels re-entered the market, some others changed their pricing structure). Indeed, our investigation focused on what hotels did, when they did it, and why.

This focus on the heterogeneity in reactions is built within a consistent theoretical framework, therefore contributing to the literature on the use of revenue management and dynamic pricing in hospitality (Abrate, Fraquelli, & Viglia, 2012; Melis & Piga, 2017) and on price-setting processes (Ellison, Snyder, & Zhang, 2018). The closest papers to our study are Wu, Zhang, Law, and Zheng (2020), who analysed Hong Kong room rates fluctuations during the COVID-19 outbreak, showing a tendency for prices in 4-star hotels to decline significantly, and Polemis (2021), who studied the performance of the hotel sector in Italy during the pandemic.

2. The COVID-19 outbreak in Italy[4]

The COVID-19 outbreak in Italy started on January 31, 2020, when two Chinese tourists in Rome tested positive for SARS-COV2. On the same day, the Italian government stopped all flights to and from China and declared a six-month state of emergency. The first domestic case without a direct connection to China was detected on February 20 in Codogno, a town 60 km southeast of Milan. It led the Italian government to impose the quarantine in 11 municipalities on February 21. On February 24, containment measures were introduced in Italy's Northern regions, where schools, cinemas, theatres, and clubs were closed, and social and sports events cancelled. Following the disease's spread, restrictions in the Northern regions were tightened on March 1 and then extended to a lockdown for the whole country on March 9.

Regarding the economic activity, the most substantial lockdown phase began on March 22, when the government declared that only "essential production" could continue, with non-essential activities being either closed or continuing from home in the smart-working mode. The list of essential activities included the delivery of goods and services related to "basic needs" (e.g., food, health, energy, administration) and the primary inputs used in their production (Manasse, Minerva, Patuelli, & Zirulia, 2020). The Italian Statistics Office (ISTAT) estimates that 55% of Italian firms continued their activity during the lockdown, although the majority suffered a significant drop in turnover (https://www.istat.it/it/archivio/244378). Hospitality was included in the list of essential activities, allowing resident and non-resident health workers (called on duty in the most heavily affected regions) and other essential workers to stay overnight outside their residence in case of strict necessity. Overall, ISTAT estimated that the Italian hospitality industry lost 52% of its turnover in the first nine months of 2020 (88% in the second quarter only, https://www.istat.it/it/archivio/250918).

The lockdown period was initially planned from March 22 to April 14, but on April 1, the government decided to postpone the end to May 4. During the lockdown, citizens not working in essential sectors could exit their dwellings only for necessary activities (e.g., walking the dog, shopping in nearby markets) under strict police enforcement. The number of new daily cases reached a maximum of 6557 on March 21, while the maximum number of daily deaths peaked at 969 on March 27.

The improvement of health conditions led to reopening many activities, under strict safety protocols, from May 4, while retail trade activities were restored on May 18. In this fortnight, citizens were only allowed to have daily excursions within their administrative regions. Finally, on June 3, interregional mobility resumed, marking the end of the most severe phase and allowing Italians to travel freely. On that day, there were 321 new cases of COVID-19 and 71 deaths.

The situation significantly improved during the summer, with only dozens of new daily cases and deaths being stable below 10 per day. At the end of August, the situation started worsening again: August 22 was the first day since May 12, with more than 1000 new daily cases, with daily deaths exceeding 10 since August 26. Our analysis ends on September 21, leaving out the second wave of the pandemic, hitting Italy since the beginning of October. On October 30, the Italian government introduced new mobility restrictions and limitations in economic activities, giving life to the second period of semi-lockdown, this time differentiating by administrative regions. On March 21, 2021, Italy recorded 104,942 deaths over 3,376,376 official cases since the beginning of the pandemic.

Table 1 reports the most important dates and phases related to the COVID-19 outbreak in Italy. Phases are labelled following the empirical analysis of Section 5. We put in italics those dates which, although not corresponding to significant moments of the pandemic or actual changes in mobility limitations, are essential in releasing information to hotel operators and customers. Weeks are numbered sequentially, starting from January 1, 2020, which is the beginning of week 1.

3. Theory and hypotheses

This section develops five hypotheses that guide the empirical

[3] Hotels also reacted in other ways to the shock, e.g., by innovating (Sharma, Shin, Santa-María, & Nicolau, 2021; Shin & Kang, 2020).

[4] Accounts of the early phase of the COVID-19 pandemic in Italy are in Remuzzi and Remuzzi (2020). The Italian Government website (http://www.governo.it/it/coronavirus-misure-del-governo) reports (in Italian) the chronological sequence of the emergency regulations.

Table 1
Phases of the COVID-19 outbreak in Italy.

Phase	Weeks	Key dates and phase description
Phase 0	Weeks 1–7	January 1 (week 1): start of our investigation. This phase ends with the first case detected in Codogno.
Phase 1 (pre-lockdown)	Weeks 8–10	*February 20 (week 8): the first case of COVID-19 without a direct connection to China was detected in Italy*. February 21: the first government decree was approved.
Phase 2 (lockdown)	Weeks 11–17	March 9 (end of week 10): start of the first national lockdown phase: schools, cinemas, theatres, and clubs were closed, social and sports events were cancelled. March 22 (week 12): full lockdown phase, and all non-essential activities were closed (hotels could decide to stay open). *April 1 (week 14): a government decree-law was announcing April 14 as the end of the lockdown. April 26 (week 17): a government decree-law was postponing the partial reopening on May 4.*
Phase 3 (transition)	Weeks 18–22	May 4 (week 18): partial reopening (under strict safety protocols) of most economic activities (excluding retail trade). May 18 (week 20): reopening of all the remaining economic activities, including retail business.
Phase 4 (post-lockdown)	Weeks 23–33	June 3 (week 23): freedom of movement and possibility to stay overnight outside own administrative region. June 12 (week 24): reopening of sports events, cinemas, and theatres.
Phase 5 (pre-second wave)	Weeks 34–38	*August 23 (week 34): insurgence of new cases and beginning of a general discussion about the arrival of the pandemic's second wave*. September 14 (week 37): reopening of schools in most Italian regions, including Lombardy.

analysis of Section 5 and concern three hotel business decisions: i) the pricing strategy; ii) the decision to stay open or not; iii) the management of cancellation policies, affecting both the type of fares offered and the level of the cancellation premium. Regarding the first two decisions, we use the monopolistic competition framework (Chamberlin, 1949), arguably the most appropriate market structure to describe the hospitality market. Accordingly, firms offer differentiated products and enjoy market power, thus changing prices in reaction to variations in demand and cost conditions. At the same time, the number of active competitors is also expected to vary, with (temporary) entry and exit in response to profits or losses realised in the market.

More formally, we adapt the framework of Krugman, Obstfeld, and Melitz (2018) and summarise monopolistic competition through two equations. The first equation is the price curve $p(n;S,c)$, which relates the price p chosen by firms (assumed to be symmetric) to the number of firms active in the market (n), to market size (S), representing the level of demand, and to the unit production cost (c). It is assumed that p is negatively influenced by n (which determines the intensity of competition) and positively affected by S and c. The second equation is the average cost curve $AC(n;S,c)$. It is assumed that the AC is positively influenced by n and negatively by S: for given market size, the presence of more firms in the market reduces the sales of each firm, thus increasing the incidence of fixed costs. Similarly, for a given n, an increase in S leads firms to spread the fixed costs over a larger quantity. Finally, c has an obvious positive impact on AC. Assuming free entry and exit in the market, the equilibrium condition is $p = AC$, with firms obtaining zero profits.[5] In Fig. 1, solid lines identify the initial equilibrium (p_0*, n_0*).

Any shock in S and c is expected to perturb the initial equilibrium, leading to an adjustment in both p and n. However, these adjustments are not equally fast: firms may be quicker in varying their price strategy than their decision to continue or temporarily cease the operations (Sutton, 1991). Suppose that, at the pandemic outbreak, a sudden decrease in demand is observed, and the number of active hotels is fixed. This corresponds to the *short-run* reaction represented in Fig. 1, where the price and the average cost curve become $p'(n;S,c)$ and $AC'(n;S,c)$ respectively (dashed lines) and the price is p_1*.[6] This situation leads to the following hypothesis:

H1. "At the beginning of the pandemic, prices decrease following the sudden drop in demand"

Suppose that the number of active firms can also adjust, which we define as the *long-run* reaction. We consider two scenarios. In the first scenario, the price curve coincides with the price curve in the short-run (dashed line). Since $p < AC$ at n_0*, the number of firms must drop, with firms exiting the market; thus, the competition gets less intense, pushing up prices and favouring the economic viability of those firms staying in the market. In Fig. 1, the equilibrium is (p_2*, n_2*) and shows a higher price, jointly with a lower number of firms.

The second scenario considers the possibility that, during the pandemic, hotels may be reluctant to increase their prices if they fear that consumers would perceive the increase as unfair (Kahneman, Knetsch, & Thaler, 1986; Mauri, 2007; Sahut, Hikkerova, & Pupion, 2016). Recently, Zhang, Hou, and Li (2020) have shown in an experimental setting that risk aversion is the underlying process through which an infectious disease can lead to a more negative emotional response to disadvantaged price inequality. In Fig. 1, this corresponds to a discontinuity at (p_1*, n_1*) such that the price does not increase above p_1* as the number of firms decreases below n_1* (dotted line). The new equilibrium in this scenario is then (p_3*, n_3*).Hence, if the price cannot adjust upwards for fairness concerns, the number of firms must decrease more significantly for $p = AC$ to hold.

In conclusion, three hypotheses on the number of active hotels and their price strategy can be tested:

H2. "The negative demand shock induced by the pandemic leads to a decrease in the number of active hotels in the market."

H3a. "During the pandemic, prices increase because of less intense competition and the increase in costs."

H3b. "During the pandemic, prices remain constant due to the perceived unfairness of a price surge".

As for the management of cancellation policies, the proper setting of rate restrictions helps balance the interests of hotels and customers (Guillet, Liu, & Law, 2014). The simultaneous offer of FC and NR options guarantees hotels to hedge, at least partially, against cancellation risk while helping to screen consumers based on their risk perception (Courty & Hao, 2000; Escobari & Jindapon, 2014) and, consequently, on their willingness to pay for the refundability option (Masiero, Heo, & Pan, 2015).

During the pandemic, risk and demand uncertainty were exceptionally high, especially during the transition towards the lockdown (where little was known about the seriousness of the health situation) and out of it, where high uncertainty was surrounding the Government interventions (notably, the ones concerning travel limitations) and their timing. In these moments, it is expected that hotels would manage the surge in risk in two ways. First, by increasing the offer of FC options, which become particularly attractive for customers. Second, by increasing the risk premium, defined as the ratio between FC and NR prices. In fact, on the one hand, higher risk pushes customers to pay more for the refundability option; on the other hand, firms are expected to discount more the NR tariff to face the increased risk with late

[5] In equilibrium, profits are zero in the sense that firms obtain the market rate of return on invested capital.

[6] In the case of COVID-19, safety protocols require time to be introduced, so it can be argued that costs are initially unaffected.

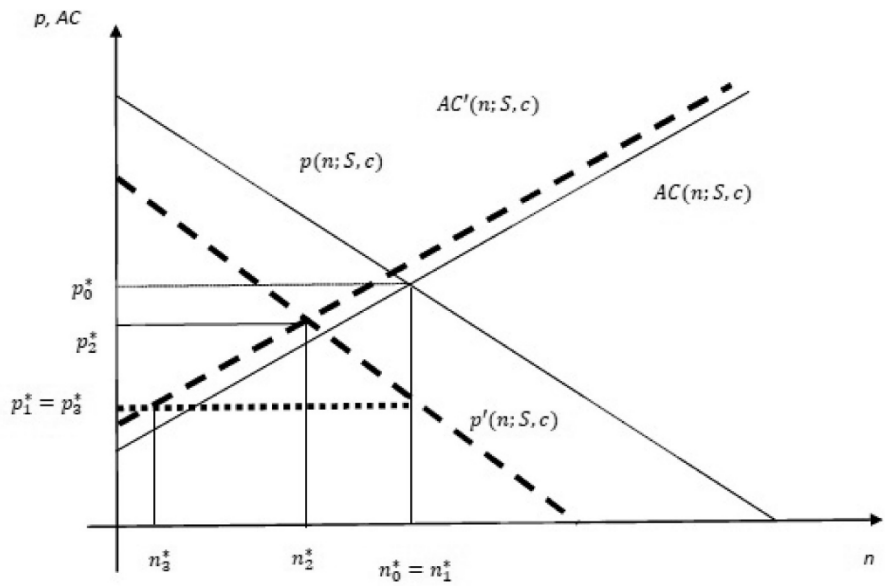

Fig. 1. Short- and long-run reaction to a negative demand shock.

cancellations. This line of reasoning leads to the following hypotheses:

H4. "The relative number of FC options increases during the pandemic to adjust for higher uncertainty in tourism demand."

H5. "The cancellation risk premium surges during the pandemic to hedge against the increased risk of late cancellations stemming from pronounced uncertainty."

4. Data and methodology

We analysed the case of Milan, the financial and economic capital of Italy and an important business destination. In 2019 the city hosted more than 8 million tourists (4.5 million were foreigners) in the 52,322 bed-places of its 474 hotels (142 of which are 4-star hotels, the most popular category in the city).

The data were collected from January 1, 2020, to September 21, 2020, and originated from a popular booking engine, Booking.com. They are related to 4-star hotels located within 5 km from the city centre of Milan, a selection yielding a population of 104 hotels that posted offers online during the timespan of interest. Restricting to 4-star hotels identifies a population in which revenue management capabilities are presumably sophisticated (Melis & Piga, 2017). To avoid any bias stemming from within-population heterogeneity (Sánchez-Pérez, Illescas-Manzano, & Martínez-Puertas, 2019; Sánchez-Pérez, Illescas-Manzano, & Martínez-Puertas, 2020), we focused on the offer of superior (or similarly defined) double rooms with breakfast included for a one-night stay. Every day, a scraper collected the characteristics of the offer and the room price (for both FC and NR options) for selected booking lead times: 0, 2, 7, 14, and 28 days.

Only for those hotels where both FC and NR fares were available, the cancellation risk premium RP, simply defined as the ratio between the two prices, was computed as in [1]:

$$\mathrm{RP} = \mathrm{P_{FC}}/\mathrm{P_{NR}} \tag{1}$$

To avoid distortions, we carefully excluded offers at excessively high rates (identified as € 500 or above per night) posted by hotels following a strategy of virtual channel closure.

Data were first scrutinised graphically. Daily figures were averaged out over the week of reference (from Wednesday to next Tuesday) to get rid of intra-week variations stemming, for example, from weekend effects. This procedure yielded 38 weekly observations in the period under investigation, from week 1 (starting on Wednesday, January 1) to week 38 (ending on Tuesday, September 21). We observed the weekly trend in the share of active hotels (i.e., hotels that offered rooms for different lead times) and posted prices, connecting them to the different phases of the lockdown. To keep the graphs intelligible, we selected four lead times to focus on immediate booking (0 and 2 days, respectively when looking at hotels' activity and prices), short-term booking (7 days), medium-term booking (14 days) and long-term booking (28 days). Mean comparison across phases using daily data were also introduced to clarify situations when visual detection was inconclusive.[7]

Econometric analysis was also performed to investigate price and cancellation premium dynamics, i.e., to test H2, H3a/b and H5 and provide robustness analysis. We estimated via OLS two hedonic price models using daily data: [2] and [3].[8] Regressions were run separately for different tariff/price index (FC, NR, RP) and alternative advance bookings (or lead times); namely, prices (and related information) posted τ days before the check-in date were used in each regression (with $\tau = 2, 7, 14, 28$).

$$Price_{it} = \alpha_i + \sum_{p=0}^{5} \beta_p Phase_{pt} + \sum_{m=2}^{9} \mu_m M_{mt} + X_{it}\gamma + \varepsilon_{it} \tag{2}$$

$$Price_{it} = \alpha_0 + \alpha_i + \sum_{p=0}^{5} \beta_p W1\_Phase_{pt} + \sum_{m=2}^{9} \mu_m M_{mt} + X_{it}\gamma + \varepsilon_{it} \tag{3}$$

In models [2] and [3], *Price* is the price index (alternatively, *FC* price, *NR* price or *RP*) posted by hotel i on day t for a check-in date $t + \tau$, α_i stands for the hotel fixed effect; $Phase_{pt}$ is a set of dummy variables taking value 1 if day t falls within the boundaries of $Phase_p$ (described in Table 1), 0 otherwise (with $p = 0, \ldots, 5$); M_{mt} is a set of monthly dummies (with $m = 2, \ldots, 9$ for February–September respectively, January is taken as a base month) to account for seasonal effects; X_{it} is a vector of control

[7] Since the analysis was performed at the population level, statistical inference was not applied.

[8] Please note that the dataset was treated as a pooled cross-section and not as a panel, since the observation unit was the offer rather than the room. Although we controlled for a series of room characteristics, thus allowing us to follow the evolution of comparable offers over time, the data at hand did not allow selecting the same room. In addition, the highly unbalanced structure of the dataset also precluded the meaningful application of panel data techniques.

variables including: *num_facil*, to control for differences in room quality; *room_avail*, a room availability index; *lim_offer*, a dummy taking value 1 if the price was advertised as a special discount, and 0 otherwise; *view*, equal to 1 for a room with view and 0 for rooms without this feature, *weekend*, a dummy taking value 1 if the check-in date was Friday or Saturday (0 otherwise), to control for the weekend effect; N_hotels_t (specific for each type of tariff), a variable indicating how many hotels were offering the same kind of fare on day t for the lead time τ, to control for market competition. Model [3] differs from model [2] because $Phase_p$ is replaced by $Phase_p\_Week\_1$, a dummy variable taking value one only during each phase's first week. This way, we focus on any abrupt change in prices in the transition of phases. Table 2 reports the descriptive statistics for the variables used in the investigation.

An important caveat is in order. Using Booking.com data neglects those transactions occurring between hotels and the national and regional governments, to offer accommodation for health professionals or to quarantine patients needed to be isolated but not in critical conditions, which have been significant during the months of the pandemic. However, when structures were operating as "COVID hotels", they were not open to the public and not active in the hospitality market. Moreover, although extremely unlikely, we cannot exclude that some hotels were open via offline channels only (by phone or e-mail) to directly share more information with potential customers.

5. Facts and findings

This section discusses the evidence related to the availability of rooms, prices, and cancellation policies over the analysed timespan. The graphical analysis is organised by phase (from Subsection 5.1 – Phase 1 to Subsection 5.5 – Phase 5), followed by the econometric analysis reported in Subsection 5.6. Fig. 2 reports the share of hotels accepting reservations out of the total population under investigation, while Figs. 3 and 4 report the weekly average of daily prices for FC and NR offers, respectively. The overall share of FC offers over the total volume of offers is presented in Fig. 5, while the risk premium, computed following eq. [1] for different lead times, is in Fig. 6.

5.1. Before the lockdown, phase 0 and phase 1

Until the detection of the first case in Codogno (week 8), availability and prices were signalling a business-as-usual situation, with 70–80% of hotels offering immediate reservations (i.e., for the same day), likely implying that the remaining 20–30% was fully booked, a typical situation in the peak business season. Accordingly, prices were unstable, reflecting important events happening on specific dates (e.g., a fashion-related event in week 8, which explains the negative peaks of availability in Fig. 2 and the positive peaks of prices in Figs. 3 and 4 for the 7-, 14- and 28-day lead times, respectively posted in weeks 7, 6 and 4).

Fig. 5 shows that, until week 8, the share of FC offers was around 0.5, i.e., hotels typically offered both FC and NR fares for the same type of room. A reduction to 0.4 was observed in week 7, corresponding to the demand peak, as hotels withdrew the FC option when the occupancy rate was sufficiently high in the proximity of the check-in date. Fig. 6 shows that the risk premium was relatively stable across different lead times, with the premium being around 10% of the corresponding NR fare.

After the first case of February 21 in Codogno (week 8), Fig. 2 shows that the fraction of hotels offering immediate bookings increased, likely due to a contraction of reservations. In contrast, prices fell for both FC (Fig. 3) and NR offers (Fig. 4). This is consistent with H1 concerning hotels' immediate reaction when facing a demand reduction. In this respect, Table 3 shows that the difference in prices before Codogno (weeks 1 to 7) and in the two subsequent weeks (weeks 8 and 9, still before the lockdown) is relevant, as prices dropped by around € 20–30 for both FC and NR options. On the contrary, cancellation policies were barely affected in this phase, possibly reflecting a limited change in risk perception. The share of FC offers remained stable at 0.5 (Fig. 5), while the cancellation premium stayed close to 10% for all lead times (Fig. 6 and Table 3).

5.2. The lockdown, phase 2

The Government decree-law of March 9 (week 10) and the introduction of the lockdown (week 12) on March 22 marked a discontinuity. They produced a dramatic reduction in demand due to the introduction of mobility restrictions. According to the theoretical framework of Section 3, this phase corresponds to the long-run reaction, where the hotel can also decide to (temporally) close.

Consistently with H2, the share of hotels offering immediate bookings (i.e., hotels that stayed open) dropped to less than 20% of the total (Fig. 2, weeks 10 to 12). The share of hotels accepting bookings at 7, 14 and 28 days is arguably linked to expectations regarding the pandemic's evolution and clues about future regulations. In this respect, three things can be highlighted: one, the share of hotels accepting future reservations was higher than the corresponding share for immediate bookings, especially for the 28-day lead time (around 80%). This evidence may suggest that hotels were relatively optimistic on the possibility of returning to "normality", or, at least, they were reluctant to take a definitive stance on future (although relatively close) dates. Two, there was a peak in the share of active hotels in week 15 (7-day lead) and week 14 (14-day lead, Fig. 2): this is likely linked to expectations that the lockdown was ending on April 14 (week 16), the date that the government initially indicated. Once the pandemic evolution made it clear that the lockdown would continue, this share dropped again. Three, there was a further peak in the percentage of hotels accepting reservations for the post-lockdown period, reaching almost 70% for the 14-day lead time (week 17) and over 80% for the 28-day lead time (week 15). This share fell again after the Government decree-law of April 26 (week 17), indicating that the end of the lockdown on May 4 would have changed nothing in travel mobility. This explains the further drop of the share to almost 20% (7-day and 14-day lead times) and less than 40% (28-day lead time) from weeks 19–20.

Moving to prices, Figs. 3 and 4 show that, after the massive drop in the pre-lockdown phase, prices timidly grew, the average absolute difference with phase 1 never being more than € 8 (Table 3). In other words, it appears that prices were relatively stable after the short-term reaction at the beginning of the emergency period. We interpret this result as a support for H3b: notwithstanding reduced competition, hotels did not attempt to limit losses by increasing prices. We argue that this could be motivated by fairness considerations.

The last point to be discussed refers to cancellation policies. At the beginning of the lockdown, uncertainty was at the highest level, and people were trying to anticipate the evolution of the pandemic and the possible introduction of travel limitations. In line with H4, Fig. 5 shows that the share of FC offers was increasing in the lockdown phase for all lead times. Regarding the risk premium (Fig. 6), a relevant increase was detected when the lockdown began (weeks 11 to 13), as predicted by H5, but only for the short-term lead (2 days), which increased by 2.7% during phase 2. The stability of premia for the other lead times seems consistent with the results on room availability, with hotels expecting (or hoping) to return to normal market conditions relatively soon.

5.3. The transition, phase 3

The transition to the post-lockdown started on May 4 (week 18). Fig. 2 shows that the availability of rooms did not increase because the government's late decision was to keep severe restrictions on mobility and work activities for a few weeks more (up to week 23). Consequently, the positive expectations built around the end of the lockdown were shattered after the Government decree of April 26. The share of hotels offering immediate availability never went over 20% in weeks 18–22. Fig. 2 also shows that for longer advance bookings (28-days lead), only

Table 2
Descriptive statistics.

Var. name	Description	Obs	Mean	Std. Dev.	Min	Max
PFC	free cancellation price	55,365	168.28	62.15	52	499
PNR	non-refundable price	35,371	161.03	63.13	47	499
premium	P_{FC}/P_{NR}	30,550	1.113	0.066	1	1.813
lim_offer	if advertised as a special offer	59,951	0.001	–	0	1
room_avail	equals to 1/X if an offer contains "only X rooms left on our website", 0 otherwise	59,951	0.032	0.125	0	1
view	if facilities or room description mention any room view	59,951	0.568	–	0	1
num_facil	number of facilities mentioned in the room	60,186	30.87	8.39	1	71
weekend	equals to 1 if the check-in date is on Friday or Saturday, 0 otherwise	60,186	0.295	–	0	1
N_hotels (PNR)	number of hotels offering P_{NR} tariff	60,180	45.65	25.91	1	87
N_hotels (PFC)	number of hotels offering P_{FC} tariff	60,186	65.63	22.49	4	99
N_hotels (premium)	number of hotels offering both tariffs	60,097	40.10	26.07	1	87

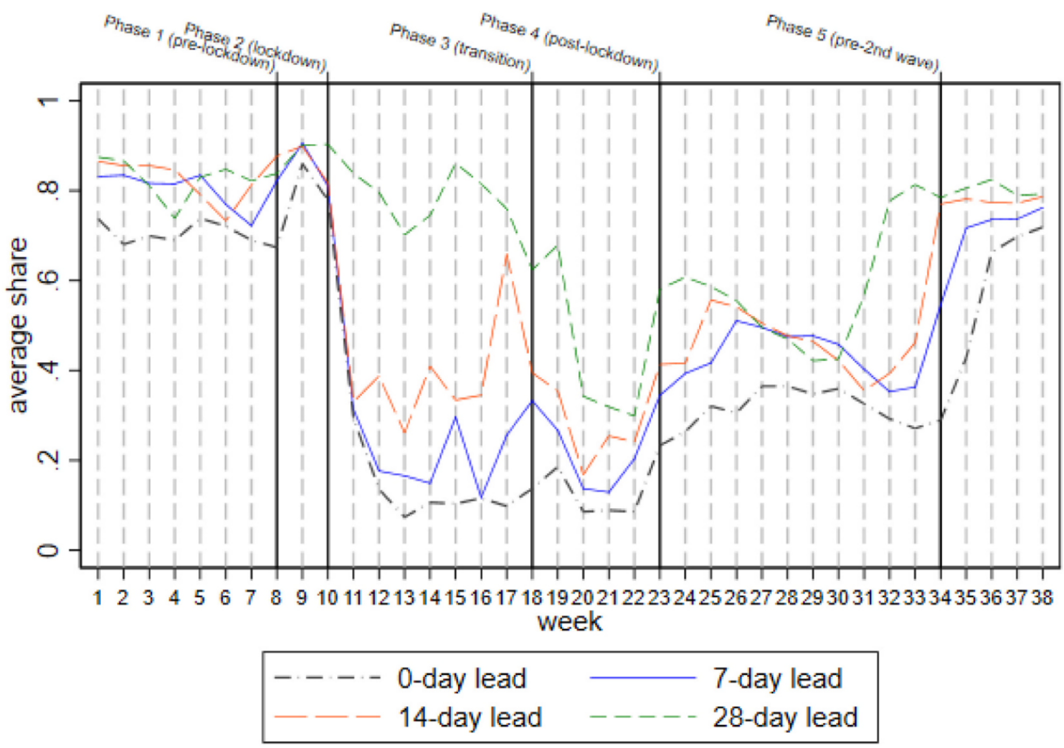

Fig. 2. Share of hotels with offers, different lead times: (0, 7, 14, 28 days), weekly averages.

less than 40% of hotels accepted reservations in weeks 20–22. Hence, at the end of May, most hotels were still on standby, waiting for more precise information about regulations and protocols to be implemented and more data about how strong the demand recovery would be.

Figs. 3 and 4 show that, in this period, prices were decreasing. This negative trend is relevant for the FC option, especially for the 2-day lead (Table 3), and marginal for the NR fares (except for the 2-day lead, which recorded a drop of 5.5%). As for the cancellation premium, a quantitatively relevant reduction is only observed for the 2-day lead, which returned to its pre-lockdown level (Fig. 6). Consistently with H4, the fraction of FC fares continued to increase (especially for short leads, Fig. 5).

5.4. The post-lockdown, phase 4

The post-lockdown phase effectively started on June 3 (week 23), reopening regional borders and the possibility of travelling and staying overnight outside own residence. The removal of travel restrictions corresponded to the beginning of the summer. Milan discounts a seasonal effect in this respect, as the city shuts down in August, and business-related activities usually restart in September. Although hospitality demand is typically lower in the summer months, most hotels stay open (in fact, only seven of the 104 4-star hotels monitored for this research had closed for holidays in the two central weeks of August 2019). In contrast, it is striking to observe in Fig. 1 that less than half of hotels accepted reservations during the whole summer 2020 and that this share increased only for September dates (weeks 35 and 36 for immediate bookings, with an anticipation of one, two and four weeks for 7-, 14- and 28-day leads respectively).

In this phase, the prices dynamics (Figs. 2 and 3) shows that both FC and NR fares decreased compared to the previous period; Table 3 reports drops ranging from 4.2% to 12.6%. Overall, the average FC and NR prices in the post-lockdown phase were between 18% and 25% lower than the corresponding prices in the pre-pandemic period, depending on the lead time. Regarding cancellation policies (Fig. 5), from the beginning of June (week 23), a divergence between immediate bookings

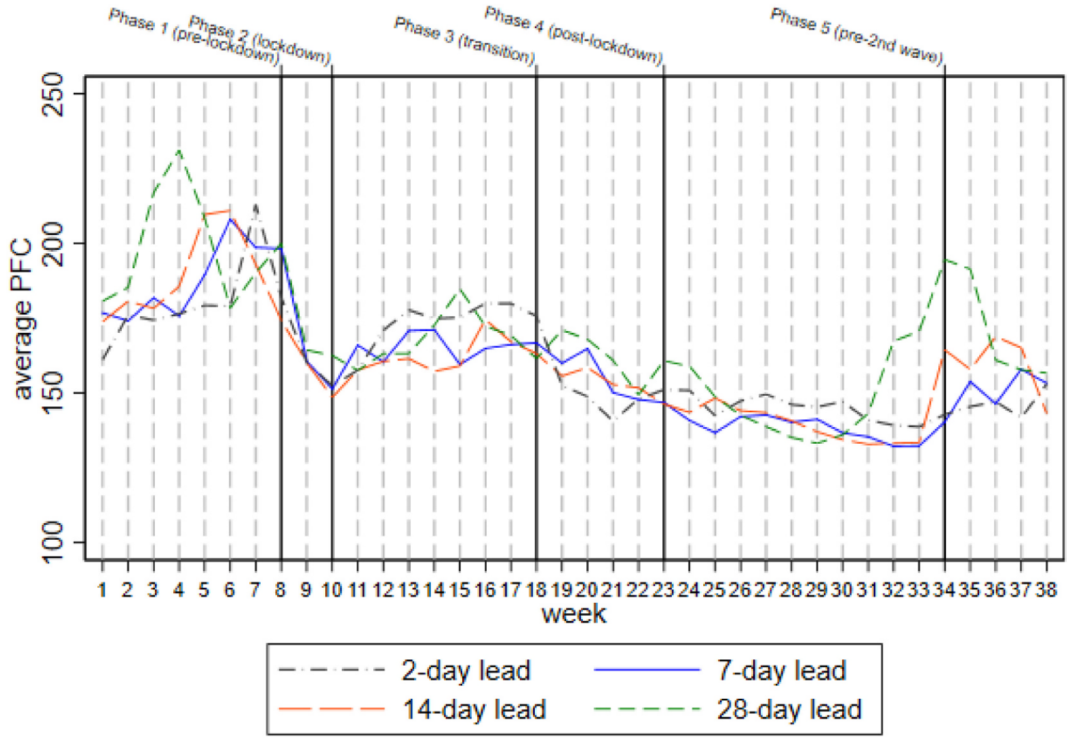

Fig. 3. Price of free cancellation offers at different lead times (2, 7, 14, 28 days), weekly averages.

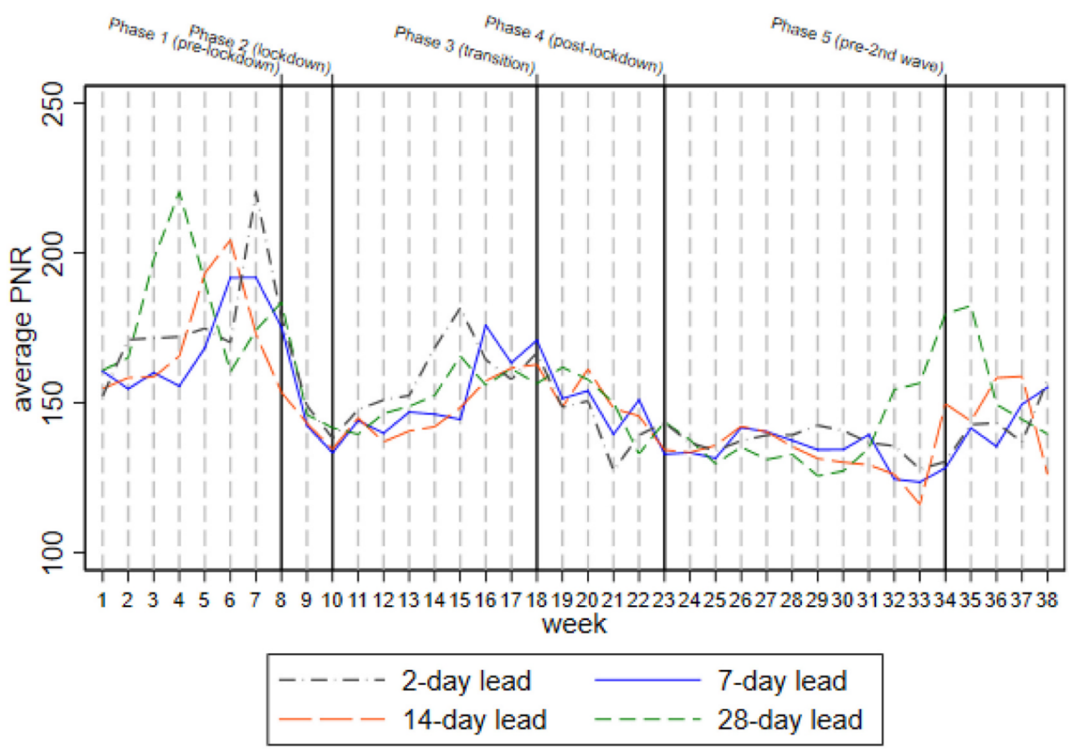

Fig. 4. Price of non-refundable offers at different lead times (2, 7, 14, 28 days), weekly averages.

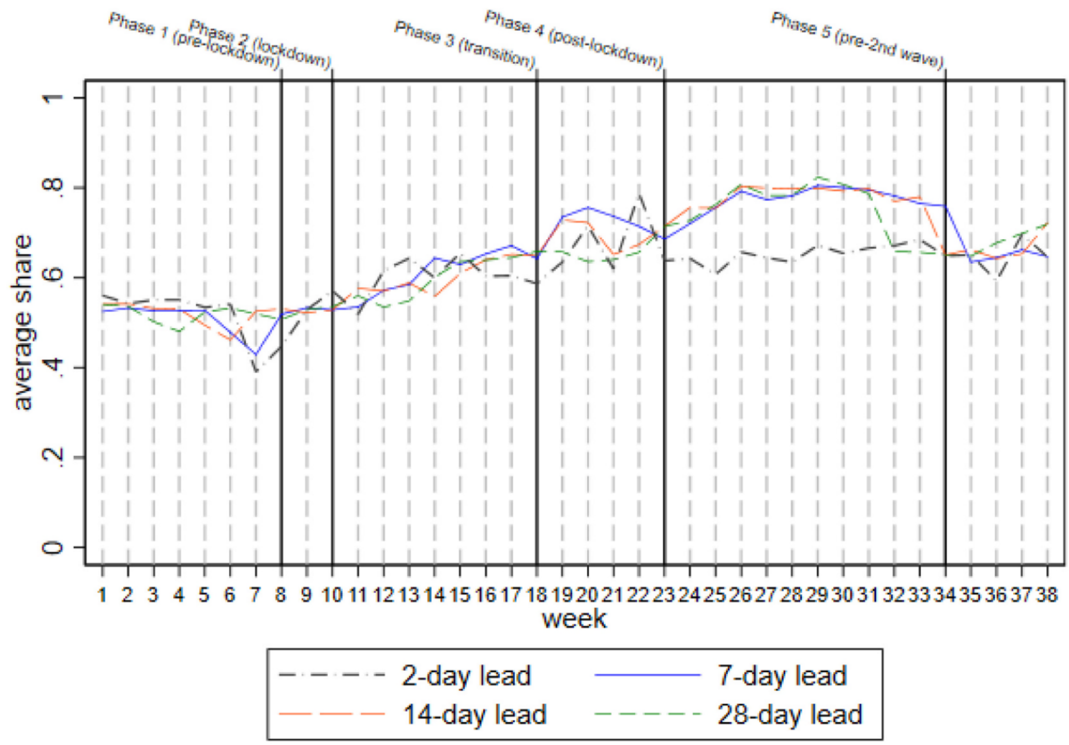

Fig. 5. Share of free cancellation offers over the total at different lead times (2, 7, 14, 28 days), weekly averages.

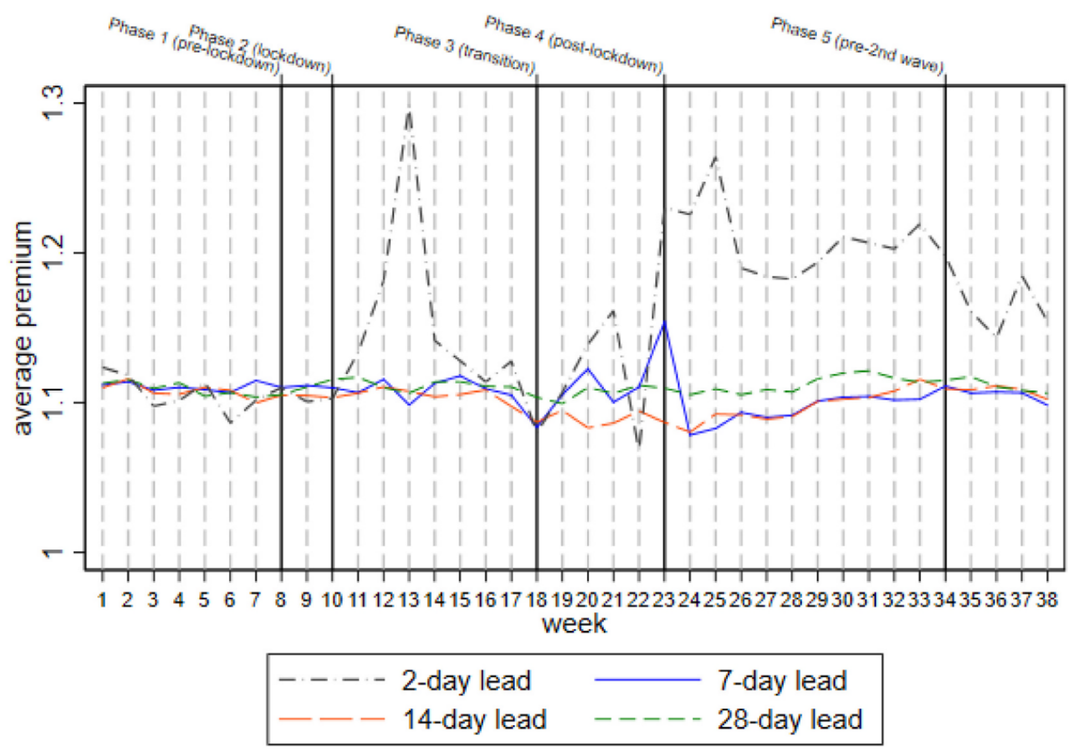

Fig. 6. The risk premium at different lead times (2, 7, 14, 28 days), weekly averages.

Table 3
Mean comparison across phases (and percentage change to the previous phase).

PFC						
Phase	Phase 0 (pre-COVID)	Phase 1 (pre-lockdown)	Phase 2 (lockdown)	Phase 3 (transition)	Phase 4 (post-lockdown)	Phase 5 (pre-second wave)
2-day lead						
N of observ.	2825	1127	756	332	2602	1640
mean PFC	178.1	162.6	170.1	151.9	145.5	146.2
		(−8.7%)	(+4.6%)	(−10.7%)	(−4.2%)	(+0.5%)
7-day lead						
N of observ.	4016	1545	1338	593	3313	2032
mean PFC	185.8	167.5	164.5	157.7	139	152.8
		(−9.8%)	(−1.8%)	(−4.1%)	(−11.9%)	(+9.9%)
14-day lead						
N of observ.	4218	1538	2295	827	3600	2267
mean PFC	188.8	159.8	162.2	155.8	141.6	160.2
		(−15.4%)	(+1.5%)	(−3.9%)	(−9.1%)	(+13.1%)
28-day lead						
N of observ.	4228	1614	4466	1310	4501	2388
mean PFC	200.2	167.2	168.8	163.9	151.6	171.6
		(−16.5%)	(+1.0%)	(−2.9%)	(−7.5%)	(+13.2%)

PNR						
Phase	Phase 0 (pre-COVID)	Phase 1 (pre-lockdown)	Phase 2 (lockdown)	Phase 3 (transition)	Phase 4 (post-lockdown)	Phase 5 (pre-second wave)
2-day lead						
N of observ.	2544	1003	527	170	1386	897
mean PNR	177.0	152.2	156.7	148.1	138	142.8
		(−14.0%)	(+3.0%)	(−5.5%)	(−6.8%)	(+3.5%)
7-day lead						
N of observ.	3797	1370	914	229	981	1073
mean PNR	168.6	147.8	149.9	153.3	134	140.7
		(−12.3%)	(+1.4%)	(+2.3%)	(−12.6%)	(+5.0%)
14-day lead						
N of observ.	3859	1391	1516	388	1080	1145
mean PNR	171.3	141.7	147.4	150.5	134.5	147.2
		(−17.3%)	(+4.0%)	(+2.1%)	(−10.6%)	(+9.4%)
28-day lead						
N of observ.	3901	1436	3028	704	1582	1136
mean PNR	183.8	147.6	151.3	153.1	142.4	160.5
		(−19.7%)	(+2.5%)	(+1.2%)	(−7.0%)	(+12.7%)

Premium						
Phase	Phase 0 (pre-COVID)	Phase 1 (pre-lockdown)	Phase 2 (lockdown)	Phase 3 (transition)	Phase 4 (post-lockdown)	Phase 5 (pre-second wave)
2-day lead						
N of observ.	1287	564	313	83	865	509
mean premium	1.11	1.10	1.13	1.10	1.21	1.16
		(−0.9%)	(+2.7%)	(−2.7%)	(+10.0%)	(−4.1%)
7-day lead						
N of observ.	3470	1342	833	212	864	881
mean premium	1.11	1.11	1.11	1.11	1.10	1.11
		—	—	—	(−0.9%)	(+0.9%)
14-day lead						
N of observ.	3620	1329	1443	369	986	1020
mean premium	1.11	1.11	1.10	1.09	1.10	1.11
		—	(−0.9%)	(−0.9%)	(+0.9%)	(+0.9%)
28-day lead						
N of observ.	3685	1420	2900	649	1533	1065
mean premium	1.11	1.11	1.11	1.10	1.11	1.11
		—	—	(−0.9%)	(+0.9%)	—

(where the share of FC options stayed around 60% of total offers) and the other lead times (where the share grew to approximately 80%) emerged, thus implying that most hotels were offering FC options only. This reaction aligns with H4, reflecting the increase in uncertainty related to the post-lockdown phase and the high demand instability. This phase was risky for hotels that, on average, decided to promote the FC reservation in exchange for a higher premium, especially for very short lead times, trying not to discourage doubtful visitors by offering the possibility to opt-out also as a last-minute option. The substantial increase of the risk premium for the 2-day lead (Fig. 6 and Table 3) aligns with H5.

5.5. *Towards the second wave, phase 5*

The change in expectations since the worsening of the health conditions (around week 34) depicts a modified dynamics. Fig. 2 shows that hotels were ready to return to business as usual in September, although about 25–30% of hotels in the sample were still out of the market in this period. In addition, after the rapid surge of FC and NR prices in week 35 for immediate bookings (and in weeks 34, 33 and 31 for advance bookings of, respectively, 7, 14 and 28 days), hotels were quick in reversing this decision as soon as the general situation deteriorated, new limitations were expected, and the lack of demand unfolded. This is well represented by the quick drop of the 28-day lead prices for week 35 (reservations in the last week of August for check-in dates in the last week of September, see Figs. 3 and 4). These reactions align with H1 and recall the immediate response of the sector before the pandemic, as described in Section 5.1.

Regarding cancellation policies, week 35 and the month of September brought about an attempt to return to business as usual in this dimension, with the share of FC options down to around 60% for all lead times (Fig. 5). However, the share was higher than the pre-pandemic period, signalling a long-lasting effect on the composition of offers. Furthermore, the risk premium comparison between the summer period of free movement and this last phase leading to the second wave shows the decrease of the risk premium for short lead times (2 days). In comparison, no changes occurred for longer lead times (14 and 28 days), supporting the idea that the leverage of the risk premium was implemented primarily as a last-minute management tool in the presence of a jump in demand uncertainty.[9]

5.6. Econometric analysis

In this subsection, we brought models [2] and [3] to the data to enrich the investigation of price and risk-premium dynamics. This way, it was possible to disentangle the impact of the different phases of the pandemic from confounding effects stemming, for example, from specific features of the rooms on offer, the degree of competition, and seasonal pricing. Results are reported in Tables 4 and 5 for, respectively, PFC (the price of the free cancellation option) and RP (risk-premium). The regressions for PNR (the price of the non-refundable option) did not provide additional insights compared to PFC's and were omitted to save on space; when results differ, they are recalled in the text. Each table presents two sets of four specifications, each one with the dependent variable posted for lead times of 2, 7, 14 and 28 days, respectively in Models 1, 2, 3 and 4 in the first set and Models 5, 6, 7 and 8 in the second set. The first set (Models 1–4) considered the specification of model [2], while the second set (Models 5–8) estimated model [3]. Standard errors were clustered by hotel to account for idiosyncrasies in pricing strategies at the hotel level.

Overall, the main findings of the econometric study can be summarised as follows. One, for PFC (and for PNR), the negative and significant signs of the phase dummies in Models 1–4 are consistent with the change in hotels pricing strategy, showing that prices were extremely low in phases 2, 3, and 4, even after controlling for seasonal pricing. Two, the comparison between Model 4 and Model 1 shows a decrease in the magnitude of the estimated coefficients of the phase dummies. As Model 4 was estimated on prices posted 28 days before the check-in date, this unambiguously signals that hotels were pricing with optimistic expectations, worsening as the check-in date was approaching. Specifically, it is interesting to look at the estimated coefficients of phase 5 for PFC: the coefficient was positive and significant in Model 4, not significantly different from the base value in Models 3 and 2 (respectively 14- and 7-day lead time), while it was negative and significant in Model 1 (2-day lead time). Arguably, this shows that realised market conditions were worse than those previously expected. This difference across lead times was also visible when looking at the first reaction entering the new phase (Models 5 to 8).

Regarding the control variables, the weekend dummy has a negative and significant sign, describing the typical pattern of a business destination like Milan. Moreover, the negative and significant sign of *N_hotels* shows that, as the number of competitors falls, the price increases consistently with the monopolistic competition regime. Finally, the negative and significant sign of *lim_offer* for short lead times (Models 1 and 5, 2-day lead; Models 2 and 6, 7-day lead) shows that hotels were using the advertisement of special offers as a last-minute and last-second strategy for attracting customers in these exceptional times of low demand.[10]

Although the price dynamics of free cancellation and non-refundable fares were quite similar, their absolute change might differ, indicating a possible effect on their ratio (the risk premium - RP). Table 5 reports estimates of models [2] and [3] when RP is the dependent variable. Consistently with the mean comparison analysis (Table 3), we found that the coefficients of the phase dummies were significant only in a few specifications. In this respect, it is crucial to see the positive sign of the coefficients of phase 1 and of the first week of phase 1 dummies, for 14- and 28-day lead times (Model 3, 4, 7): at the start of the period of high uncertainty, the expected shift of demand towards free cancellation fares was met with a strategy of increasing this fare relatively more than non-refundable fares. Similarly, the coefficient is positive for phases 4 and 5, 2-day lead time (Model 1), as this was a phase of recovering demand but still filled with uncertainty. Thus, hotels were attempting to shift part of the risk associated with free cancellation onto customers.

6. Conclusion

This paper provides evidence on how hotel management responded before, during, and after the lockdown introduced to fight the COVID-19 outbreak. Milan, an important business destination at the epicentre of the pandemic in Europe, was investigated. A series of five hypotheses guided our empirical analysis, which unfolded graphically and through hedonic price regressions. Findings suggest that the immediate reaction to the pandemic was to fine-tune prices, which dropped considerably. With the beginning of the lockdown, the great majority of hotels decided to stop operations, while prices of those who stayed open exhibited a significant degree of stability, a fact that can be attributed to fairness considerations. Hotels also increased the availability of free cancellation fares and (temporary) increased the risk premium for short-term leads to manage uncertainty and turbulence.

It is also important to highlight that news and expectations about the path of the pandemic and the future introduction of regulations and travel limitations were equally essential drivers of managerial decisions than actual changes in the rules. Specifically, the hedonic price analysis showed a continuous reduction of prices, ceteris paribus, when approaching the check-in date, suggesting that positive expectations regarding future demand and target occupancy rates were unmet, thereby calling for consequent policies of dropping prices. This evidence was also reinforced by the systematic use of last-minute special offers (and last-second too, when free cancellation fares were investigated) when approaching the check-in date.

Managerial and policy implications are difficult to derive at this stage due to the lack of reliable information on the change in hotels'

[9] As the number of hotels staying on the market in lockdown was much lower than the whole population, we checked whether findings presented in this Section stemmed from specific characteristics or pricing strategies of this subsample of active hotels. We hence computed average FC and NR prices, and the corresponding RP, only for the subsample of hotels that have been offering rooms for the whole period. Results were consistent: specifically, we found confirmation of the increase in the RP for the 2-day lead time in the post-lockdown compared to the pre-lockdown, as discussed above. However, the peaks shown in Figure 5 for the 2-day lead are much less pronounced (See Figure A.1 in the Appendix), suggesting that the fine-tuning of the RP was especially used jointly with the decision of entering/exiting the market.

[10] For NR offers the coefficient of *lim_offer* was significant in Model 2 and 6 only (7-day lead time), showing that non-refundable options were offered with a discount as a last-minute strategy, but not as a last-second.

Table 4
Regression results, free cancellation price as dependent variable.

	Model 1 (2-day lead)	Model 2 (7-day lead)	Model 3 (14-day lead)	Model 4 (28-day lead)	Model 5 (2-day lead)	Model 6 (7-day lead)	Model 7 (14-day lead)	Model 8 (28-day lead)
lim_offer	−36.99**	−18.07	−15.45	−8.91	−37.15**	−18.44	−16.29	−9.98
	(0.002)	(0.063)	(0.299)	(0.286)	(0.004)	(0.077)	(0.259)	(0.103)
room_avail	15.17	7.60	−0.40	2.78	17.80*	9.61	0.47	1.19
	(0.059)	(0.258)	(0.924)	(0.590)	(0.028)	(0.185)	(0.910)	(0.821)
view	11.40	8.97	9.02	19.87	12.75	10.12	10.10	20.53
	(0.345)	(0.435)	(0.469)	(0.061)	(0.284)	(0.376)	(0.402)	(0.051)
num_facil	0.57	0.17	−0.40	−0.48	0.53	0.16	−0.36	−0.43
	(0.468)	(0.909)	(0.679)	(0.570)	(0.489)	(0.912)	(0.706)	(0.612)
weekend	−9.88***	−9.10***	−6.05***	−8.39***	−10.08***	−9.58***	−8.12***	−9.02***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N_hotels	−1.05***	−0.87***	−0.40***	−0.82***	−0.78***	−0.52***	−0.38***	−0.94***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Phase 1	−14.30***	−7.05***	−35.15***	−15.52***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Phase 2	−45.40***	−49.19***	−42.69***	−26.37***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Phase 3	−65.74***	−61.23***	−42.29***	−29.71***				
	(0.000)	(0.000)	(0.000)	(0.000)				
Phase 4	−52.05***	−47.15***	−40.62***	−9.37				
	(0.000)	(0.000)	(0.000)	(0.067)				
Phase 5	−29.89***	−3.25	−5.11	27.33***				
	(0.000)	(0.680)	(0.382)	(0.000)				
Phase1_Week1					−8.46***	−2.93	−27.93***	−10.18***
					(0.000)	(0.147)	(0.000)	(0.000)
Phase2_Week1					−11.87*	−9.74**	−5.23	3.28***
					(0.017)	(0.008)	(0.184)	(0.011)
Phase3_Week1					11.51***	11.44**	12.66***	34.15***
					(0.000)	(0.002)	(0.000)	(0.000)
Phase4_Week1					−4.85*	−0.11	−0.81	12.08***
					(0.042)	(0.969)	(0.711)	(0.000)
Phase5_Week1					8.49***	28.80***	31.94***	42.60***
					(0.000)	(0.000)	(0.000)	(0.000)
constant	186.00***	223.73***	202.45***	247.56***	168.04***	191.83***	198.75***	256.64***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Hotel FE	✓	✓	✓	✓	✓	✓	✓	✓
N_obs	9223	12,804	14,741	18,586	9223	12,804	14,741	18,586
N_clusters	87	103	103	103	87	103	103	103
R^2	0.74	0.73	0.71	0.70	0.73	0.72	0.70	0.71
F-test	25.78***	32.77***	62.00***	35.08***	10.67***	24.31***	56.49***	45.66***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

F-test reports the F-statistics from a joint significance test for the phase dummy variables. *P*-values in parentheses; s.e. clustered at the hotel level. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

operational costs and performances. Should individual data on performance and hotels' balance sheets be available, research might compare hotels staying in and out of the market, thus shedding light on what was the best strategy (presumably, the one minimising losses). Theoretically, when faced with dramatic crises such as the one associated with COVID-19, the decisional model is clear (Tsionas, 2021). However, empirically, it is crucial to consider the interrelatedness between performance and decisions over prices, activity continuation, risk perception and management of uncertainty, especially in a general context of political instability. Hotels were facing increased uncertainty and risk both in case they were deciding to stay out of the market and in case they were frantically modifying their strategies to chase policy decisions, often late or contradicting. This is a key policy issue, calling for the importance of providing clear and stable information to the market, especially in these highly turbulent times. Clarity and stability of protocols and regulations are as crucial as transfers and grants when the aim is to restore trust in the future (Assaf & Scuderi, 2020).

This study is a preliminary investigation of hotels' strategies in exceptional times that are not over yet while we write. This is the main limitation of the paper, and it would be essential to update our evidence through the analysis of the entire post-lockdown period up to the end of the pandemic. Although predicting the long-term impact of the pandemic, notably on demand, is not an easy task (McKercher, 2021), solvency issues would likely hit many players in the market should the emergency continue for a long time. With a relevant number of hotels forced to go bankrupt or permanently exit the market, the competition structure could change. In such a case, it would be possible that highlanders will increase the equilibrium price also to meet higher production costs stemming from tighter safety and health regulations. Also, it may be the case that the risk premium will increase to a higher equilibrium level, as the risk and uncertainty associated with the "new normal" would be higher in case customers' behaviour were permanently affected by the health crisis (Nguyen & Coca-Stefaniak, 2021).

In this respect, an important extension of the paper would be to move to profitability considerations in line with Polemis (2021), as managerial decisions are related to expected profits or losses, compared to losses incurred by keeping the hotel close and when public transfers are available to subsidise the sector. In doing so, it would be important to access data on total revenues and occupancy rates and to estimate the increase in operational costs due to the introduction of health protocols.

Table 5
Regression results, risk premium as dependent variable.

	Model 1 (2-day lead)	Model 2 (7-day lead)	Model 3 (14-day lead)	Model 4 (28-day lead)	Model 5 (2-day lead)	Model 6 (7-day lead)	Model 7 (14-day lead)	Model 8 (28-day lead)
lim_offer	−0.015	0.005	0.002	−0.019***	−0.015	0.005	−0.003	−0.018***
	(0.398)	(0.077)	(0.633)	(0.000)	(0.445)	(0.094)	(0.413)	(0.000)
room_avail	0.000	−0.037	−0.106	−0.033	0.000	−0.038	−0.106	−0.034
	(.)	(0.064)	(0.068)	(0.108)	(.)	(0.057)	(0.067)	(0.105)
View	0.014	−0.024	−0.010	−0.022	0.014	−0.024	−0.010	−0.022
	(0.587)	(0.341)	(0.541)	(0.148)	(0.580)	(0.334)	(0.548)	(0.147)
num_facil	−0.007	0.001	0.000	−0.000	−0.007	0.001	0.000	−0.000
	(0.098)	(0.458)	(0.821)	(0.760)	(0.086)	(0.435)	(0.819)	(0.768)
weekend	0.015*	0.001	0.001	0.001	0.015*	0.001	0.002	0.001
	(0.021)	(0.367)	(0.371)	(0.568)	(0.017)	(0.318)	(0.157)	(0.442)
N_hotels	−0.001	0.000	−0.000	0.000	−0.001	0.000	−0.000	0.000
	(0.061)	(0.556)	(0.259)	(0.128)	(0.138)	(0.354)	(0.309)	(0.114)
Phase 1	0.007	0.001	0.006*	0.004*				
	(0.223)	(0.606)	(0.025)	(0.030)				
Phase 2	−0.014	−0.001	0.006	0.006				
	(0.159)	(0.851)	(0.260)	(0.084)				
Phase 3	0.001	0.009	−0.002	0.003				
	(0.963)	(0.260)	(0.773)	(0.622)				
Phase 4	0.101**	0.001	−0.002	0.003				
	(0.005)	(0.977)	(0.858)	(0.718)				
Phase 5	0.078*	−0.006	−0.006	0.003				
	(0.015)	(0.740)	(0.608)	(0.706)				
Phase1_Week1					0.005	0.000	0.005*	0.003
					(0.282)	(0.981)	(0.021)	(0.081)
Phase2_Week1					−0.017*	0.001	−0.000	0.002
					(0.031)	(0.876)	(0.934)	(0.395)
Phase3_Week1					−0.044**	−0.000	0.011	−0.005*
					(0.002)	(0.984)	(0.083)	(0.016)
Phase4_Week1					0.007	0.067	−0.008	0.002
					(0.694)	(0.117)	(0.159)	(0.485)
Phase5_Week1					0.004	−0.007*	−0.004	−0.001
					(0.622)	(0.034)	(0.115)	(0.790)
constant	1.353***	1.103***	1.117***	1.132***	1.356***	1.100***	1.116***	1.132***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Hotel FE	✓	✓	✓	✓	✓	✓	✓	✓
N_obs	3591	7544	8697	11,252	3591	7544	8697	11,252
N_clusters	50	90	90	91	50	90	90	91
R^2	0.54	0.43	0.52	0.59	0.54	0.44	0.52	0.59
F-test	2.43**	1.04	1.57	1.09	2.55**	1.97*	1.82	2.69**
	(0.048)	(0.397)	(0.176)	(0.373)	(0.039)	(0.090)	(0.116)	(0.026)

F-test reports the F-statistics from a joint significance test for the phase dummy variables. P-values in parentheses; s.e. clustered at the hotel level. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Experts of the Italian hospitality service (www.thrends-italy.com) estimate this increase around 10% of cleaning costs, a value that can be considered negligible in the balance sheet. However, the most significant increase stems from the incidence of fixed costs, which in turn depends on the occupancy rate and the strictness of health regulations and interpersonal distance protocols (Assaf & Scuderi, 2020). Regarding transfers from the government, in the Italian case, they depend on several aspects: the hotel's turnover, the loss recorded in the months of the pandemic, property taxes due, overdue mortgage. Moreover, most subsidies have not been computed and transferred yet, so this analysis is necessarily shifted to the future. In this respect, an essential extension of our work goes through the international comparison of hotels in countries differing in the structure of public transfers and health and mobility regulations.

Another limitation is that we only investigated a single online distribution channel, while hotels usually apply a diversified strategy, with offline and online channels, and across different online platforms. This limitation might trigger another extension of the study. Finally, it would be interesting to investigate other destinations that differ as regards specialisation and tourism mix. Milan is a typical business destination and discounts the easing of restrictions at the beginning of the summer, which is the low season for the city. How did cultural or leisure destinations react when the end of the lockdown matched with the beginning of the peak season? This is left to future investigation.

Declaration of Competing Interest

None.

Appendix A. Appendix

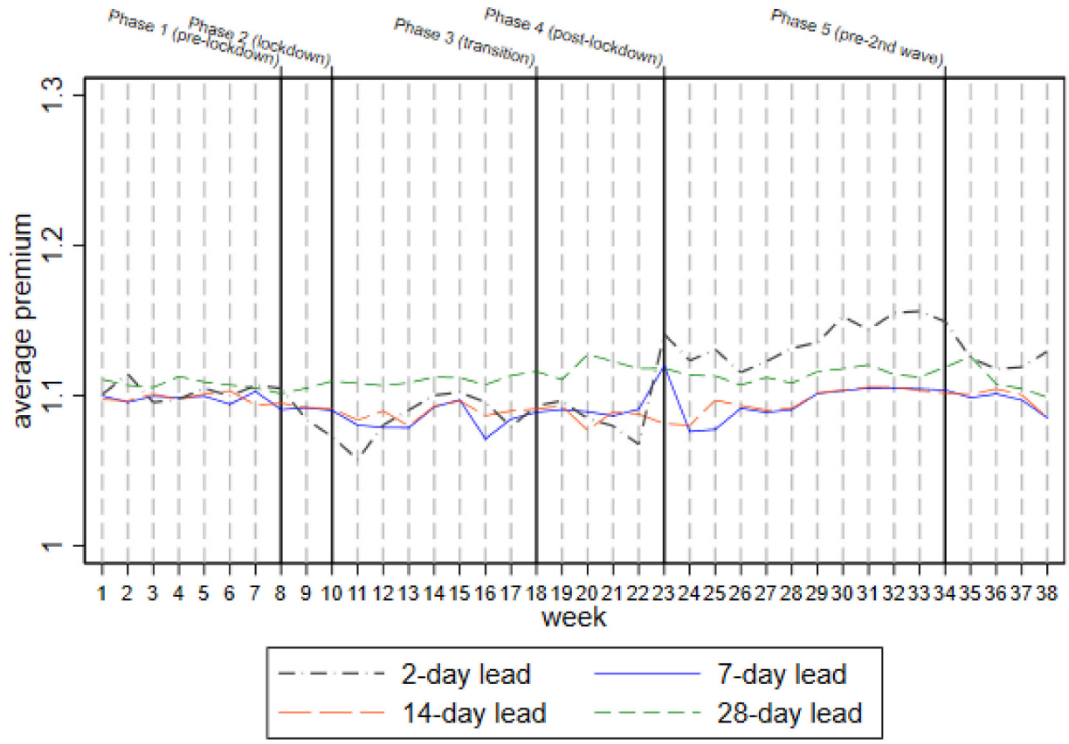

Fig. A.1. The dynamics of risk premium, different lead times: 2, 7, 14, 28 days, sub-sample of hotels always on the market in the whole period.

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