Information & Management 60 (2023) 103857

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

How to react to a shock? Effects of Airbnb hosts' choices and market segmentation at the time of Covid-19

Luigi Buzzacchi [a], Francesco Luigi Milone [b], Emilio Paolucci [b], Elisabetta Raguseo [b,c,*]

[a] Interuniversity Department of Regional and Urban Studies and Planning (DIST), The Future Urban Legacy Lab (FULL), Politecnico di Torino, Viale Mattioli, 39, 10125, Torino, Italy

[b] Department of Management and Production Engineering (DIGEP), The Future Urban Legacy Lab (FULL), Politecnico di Torino, Corso Duca degli Abruzzi, 24, 10129, Torino, Italy

[c] Aix Marseille Univ, CERGAM, Aix-en-Provence, France

ARTICLE INFO

Keywords:
Marketing choices
Price adjustments
Flexible policies
Shock
Covid-19
Market segmentation
P2P platform

ABSTRACT

We investigate the way service providers who operate on an online peer-to-peer (P2P) platform readapted their marketing choices to face the Covid-19 pandemic. Through an empirical investigation on a large dataset of Airbnb properties in Rome, observed from January 2018 to December 2020, we provide a threefold contribution by investigating how Airbnb hosts reacted to the Covid-19 pandemic shock, in terms of marketing choices, such as price adjustments and flexible cancellation policies; the direct effects of these choices on their economic returns; and how service providers on Airbnb reacted to address the new needs of their customers during the Covid-19 pandemic. The findings provide useful insights for researchers and practitioners and show that the adoption of combined marketing choices led to more than proportional effects on performances as it allowed Airbnb hosts to exploit profitable market segmentation mechanisms.

1. Introduction

The Covid-19 pandemic was an unprecedented shock that affected the economy and society as a whole. Although the tourism industry is not new to exogenous shocks [1], the Covid-19 shock was different from and more pronounced than any other shock, because it had the potential of triggering structural changes within the industrial sector [2]. In this context, the Covid-19 outbreak has been recognised as a super economic shock of the tourism industry [2], which has left a remarkable footprint on the market structure, thus paving the way for a complete strategic repositioning of the involved actors [3–7].

Drawing on the consequences of the global shock imposed by the Covid-19 pandemic, this paper investigates how a large share of accommodation service providers on the short-term rental market, namely hosts active on the Airbnb platform, coped with the Covid-19 epidemic by actively repositioning their marketing choices on the platform with the aim of meeting the customers' needs that emerged as a result of the pandemic. Market segmentation was achieved through significant adjustments of the pricing policies, in conjunction with such a modification of the functional listing attributes as flexible cancellation policies [8] with the aim of achieving consumer 'self-selection' [9].[1] This argument seems to be relevant since, due to the presence of accommodation providers on the digital platform and to the features of a platform on which service providers can leverage, such marketing choices can quickly be implemented and tested. In other words, during the Covid-19 period, the sudden need for 'behavioural' re-segmentation of the market (i.e., markets segmented by purchase occasion, benefits sought, and user status, according to the classification proposed by [10]) allowed hosts providing accommodation services on a digital platform to react quickly by adopting self-selection techniques to adjust their offer to rapid external changes.

We have focused on Airbnb hosts since, after several years of impressive growth rates, which led the digital platform to the forefront of the sharing economy and the hospitality industry [11], the company has been one of the most severely impacted by the Covid-19 outbreak, so much so that a flourishing stream of literature has concentrated on

* Corresponding author.
E-mail address: elisabetta.raguseo@polito.it (E. Raguseo).

[1] Self-selection (or 'screening') has been a central idea in the economics of information since Akerlof [47], Mirrlees [48], Stiglitz [49], and those that followed. The analogy with the market segmentation problem was obtained by interpreting each product attribute-price pair as the optimal marketing-mix to attract different (unknown) segments of the demand. An extensive discussion on the consumer market segmentation method was proposed by Goyat (2011).

https://doi.org/10.1016/j.im.2023.103857
Received 15 September 2022; Received in revised form 30 August 2023; Accepted 3 September 2023
Available online 9 September 2023

studying the impact of Covid-19 on the possible future trajectories of Airbnb [12–15].

We have investigated the set of marketing choices taken by hosts to achieve better economic returns or to reduce adjustment costs and risks. In fact, despite the general sharp decrease in the demand, and the common representation of the shock as having affected the entire touristic industry in a uniform manner, we argue that the willingness to pay, on the demand side, could have increased in specific market segments, but only when the offered services had been able to satisfy the new preferences and the new customers' habits [16]. We provide evidence that these new needs have effectively been captured by a significant number of hosts who have been able to differentiate their offer accordingly in the newly reconfigured segments. Accordingly, the research questions tackled in this paper are:

RQ1: Has the Covid-19 pandemic shock generated a widespread change in the marketing choices of service providers on accommodation digital platforms?
RQ2: What is the relationship between the marketing choices that were adopted by service providers on the accommodation digital platforms and the economic returns observed during the Covid-19 pandemic?

To address these research questions, we leveraged on a longitudinal dataset that allowed us to observe the effects of the marketing choices (price and flexible policies as functional attributes) and economic returns (occupation rates and revenues per active nights, as in line with Airbnb literature; [17]) at a single Airbnb property level in the city of Rome (i.e., the largest touristic submarket in Italy). The first evidence that emerged from these data is that the sharp market contraction due to the pandemic shock affected demand much more than supply: the negative change in revenues has in fact been about five times larger than the exit rates (see Table 1), thus depicting a novel market condition on the Airbnb platform. This circumstance suggests that competition must have increased substantially and, consequently, forced (at least some) entrepreneurs to react to the shock with renewed activism.

This evidence, which illustrates Airbnb's new market conditions, offers an interesting opportunity to study the effects of a negative shock on an online platform market, thereby complementing our understanding on the literature that has so far mainly studied platforms in periods of expansion and rapid growth. The new market conditions of Airbnb suggest the importance of marketing activism in a framework of growing and increasingly fierce competition, in the face of greatly reduced demand, against an (almost) still fully present supply. We therefore analysed the two marketing levers that seem to have been adopted most frequently, according to the data at our disposal[2]: the adoption of flexible policies as a functional attribute (which allow customers to cancel bookings with no or negligible costs) and price adjustments. In short, price and flexible policies were found to be strategic complements, i.e., the combined adoption of the two types of marketing choices generated more than proportional effects, as it allowed hosts to exploit profitable market segmentation through a screening mechanism in which customers are sorted according to their service preferences.

The rest of the paper is organized as follows: Section 2 provides the theoretical background of our work, and also revisits the main literature contributions; Section 3 develops the hypotheses; Section 4 illustrates the data and methodologies; Section 5 shows the results, and Section 6 discusses our findings and the respective contributions.

2. Theoretical background

In order to introduce the development of the hypotheses and the subsequent empirical analyses, this section provides a review of the main contributions to the literature in consideration of the research streams tackled in this paper: i) short-term rentals and the Covid-19 pandemic, and ii) price and non-price marketing choices on peer-to-peer (P2P) accommodation platforms (before and after Covid-19).

2.1. *The effects of the Covid-19 pandemic on Airbnb*

Despite having been backed by an impressive growth over the past few years, the tourism industry has been one of the hardest hit by the Covid-19 pandemic [19,20], and, being one of the most prominent players on this market [11], Airbnb has not been exempt from the tremendous shock of the pandemic.

It has been observed, starting from the pioneering contribution of Hu et al. [15], that the impact of the Covid-19 outbreak on the reservation volumes of the platform was immediate, with both the local and global demand being instantly impacted as a result of the declaration of the first Wuhan lockdown and the subsequent spread of the Covid-19 pandemic throughout the world. Dolnicar & Zare [2] referred to this situation as *"Disrupting the disruptor"*, with Airbnb, the disruptor of the accommodation services [21,11], being severely impacted by the Covid-19 pandemic.

Following the work of Dolnicar & Zare [2], multiple studies have drawn up the possible trajectories of the future of Airbnb (e.g., [14]), whereby they have mixed both quantitative and qualitative methodologies and studied the evolution of either the supply of or demand for Airbnb. Although it is not the aim of this paper to provide an exhaustive overview on the literature that has studied the effects of the Covid-19 pandemic on the short-term rental market, it is necessary to summarize the discontinuity introduced on the market by Covid-19.

Studying the demand side, Bresciani et al. [12] shed light on the migration of demand toward more isolated accommodation types (i.e., entire apartments), and showed that the possibility of renting isolated accommodation indicated a distinct feature of the platform to accommodate emerging demand needs. In this sense, the authors suggested that the availability of an isolated space can result in a form of competitive advantage for Airbnb hosts, compared to traditional hospitality service providers, given the mutated change in consumer needs [12,22]. These results have generally been confirmed by other scholars, and thus converge toward Airbnb customers paying greater attention to aspects that minimize the risks associated with the infection of the virus. To this aim, Godovykh et al. [23] showed that the information on cleanliness provided to customers had a significant effect on their intention to make a reservation, thus confirming new emerging needs in the customers' behaviour. In line with these findings, Shen et al. [24] showed that the perception of *cleaner* accommodation mitigated the impact of the Covid-19 pandemic on the revenues and occupation of service providers by significantly increasing their performance, compared to rentals perceived to be *unclean*. Apart from the consumers' perception of risk and the avoidance of risk, and in line with the issues discussed in this paper, Singh et al. [25] showed, by means of an emotional analysis, that another important determinant of customer intention is that of the cancellation options provided to customers, given the uncertainty and the impossibility of planning either leisure or business trips over the medium-long term during the pandemic.

When focusing on the supply side of the Airbnb platform, the literature has provided weak evidence of a significant proportion of multi-listing *'professional' hosts* having interpreted and reacted to the shock in a more sophisticated way (see [26], and [27], for an overview on the professional host phenomenon). Farmaki et al. [13] outlined the perception of the short-term and long-term impacts of the Covid-19 pandemic on the host community and highlighted the presence of either service providers with a more pessimistic attitude toward the pandemic situation (i.e., those willing to leave the platform), or those with an optimistic view, that is, who saw the Covid-19 pandemic as an opportunity to adjust their competitive position on the market.

[2] See Sect. 4.2.2 for a detailed discussion on why we focused on these two sets of marketing choices.

Table 1
The Pre vs Post Covid-19 pandemic scenario in Rome.

Year	Active Listings	Total Revenues	Res. Nights	Occ. Rate	RevPAN
2018	42,028	$ 439,323,137.22	3,650,895	41.35%	$ 49.75
2019	42,864	$ 508,347,172.89	4,323,335	48.79%	$ 57.37
2020	36,012	$ 121,072,214.67	1,162,574	16.34%	$ 17.02
Δ 2020–2018	−14%	−72%	−68%	−60%	−66%
Δ 2020–2019	−16%	−76%	−73%	−67%	−70%

Note: a) Source: The authors' calculations of AirDNA data. b) The data refer to the whole Roman market. The period referred to in 2018, 2019, and 2020 is 1st March to 31st December. This period was adopted to compare shock situations (i.e., March-December 2020, as in [18]) with common ones (i.e., March-December 2018 and 2019). c) Res. Nights = nights reserved in Airbnb; Occ. Rate = occupation rate (see Section 4.2.1 for the operationalization of the variable); RevPAN = revenues per active night (see Section 4.2.1 for the operationalization of the variable).

2.2. The marketing choices and economic returns of Airbnb service providers

Given the importance of understanding how the marketing and tourism management literature has investigated the impact of the tactics and the marketing choices of hosts on their economic returns, we have conducted a literature review on the antecedents of the economic returns of hosts in the P2P environment both before and during the Covid-19 pandemic. As a result, we identified a research gap in the empirical investigation on the marketing choices implemented by the hosts on Airbnb to face the Covid-19 pandemic. The literature in fact contains a multitude of research articles that have studied the different types of performances of Airbnb listings with respect to various property-level characteristics (mainly adopting hedonic-based models), and analysed the effects of peers' reputation and other structural characteristics (including the type and location of the listing) either before (see [28], for an extensive review) or after the Covid-19 outbreak. However, apart from the investigated impact of cleanliness signals on rental occupation and income [24], which represents a completely new marketing lever in the hands of Airbnb hosts, the relationship between the marketing choices of service providers and performances has mainly been studied before the pandemic, raising questions regarding the effects of specific marketing choices on economic returns after the Covid-19 outbreak.

Drawing on the existing literature, we have identified two possible groups of marketing choices that may be implemented by service providers to react rapidly on Airbnb in order to address the new needs of customers during Covid-19: a) price adjustments, in response to a modified price elasticity on the demand side, and b) service adjustments, which allow hosts to meet the modified preferences of the customers through the adoption of different reservation procedures. Looking at previous studies on the prices applied by Airbnb hosts, Gunter et al. [29] and Gunter & Önder [30] found, on the one hand, that the demand for Airbnb (in Vienna) was almost price inelastic, while Benítez-Aurioles [31] found that Airbnb demand (in Barcelona and Madrid) was price elastic. The first contributions of Boto-Garcia [32] and Hidalgo et al. [33], who zoomed into the post-Covid pandemic market, have shown that Covid-19 has introduced a pricing activism on the short-term rental platform, and have pointed out mixed results, which show either price-decrease or price-increase trends in Barcelona and Madrid, respectively. According to Farmaki et al. [13], this is a consequence of the unexpected situation that was triggered by the Covid-19 pandemic, as hosts may now decide on one choice or another to pursue different objectives.

The contradictory results reported in the aforementioned studies indicate that, in general, Airbnb's supply is confronted with a clearly segmented market and heterogeneous customer preferences that the Covid-19 pandemic has probably changed significantly. New marketing choices are therefore expected; in this sense, the service-level choices, together with a finely tuned price variable, should help to realise more economic returns from different types of customers, thus allowing hosts to segment customers according to their different degrees of willingness to pay through self-selection [34]. In particular, we draw on the hosts' discretional adoption of alternative cancellation policies: flexible, moderate, or strict, which involve from low to high cancellation costs. We interpret the hosts' decision to adopt one of these cancellation policies as a way for them to react to the new needs of customers resulting from the pandemic. Even though the empirical evidence summarized by Sainaghi et al. [28] suggests that the adoption of stricter policies, up to the pre-pandemic period, was associated with both higher revenues and higher occupation rates (with these results being confirmed by other scholars, such as [35]), the re-configuration of the customers' habits following the outbreak of Covid-19 is expected to determine a new segmentation of the demand and, consequently, new-business rules for the hosts to follow.

3. Hypothesis development

Firms are often triggered to reposition themselves whenever the industry in which they compete experiences a demand, supply, technological, or regulatory shock [36], such as is the case of the Covid-19 pandemic. Service providers can decide to readjust their price level or service characteristics as a marketing response to cope with new market conditions in order to achieve greater margins and/or higher market shares.

In our setting, Airbnb hosts can defend their economic returns in two fundamental ways. First, they can act on prices. By increasing prices they could obtain, ceteris paribus, higher unit margins, which may be useful, for instance, to mitigate the loss of revenue caused by the pandemic shock [13]. On the other hand, by reducing their prices, Airbnb hosts can expect to capture new market shares and increase occupation rates on a thinner market. Second, by increasing the value of the service they offer, Airbnb hosts can expect to increase the willingness of customers to pay or to capture emerging market segments, which may have emerged after the shock. With specific reference to the empirical setting of our work, the level of the service for the customer can be modified – amongst other decisions – by defining the flexibility of the reservation procedure. Unlike the pre-pandemic market, where stricter polices resulted in higher economic returns for hosts [28,35], more flexible cancellation policies in many market segments could profitably adapt to the emerging uncertainty caused by the main anti-contagion policies and the unpredictability of medium-long term forecasts on the spread of the Covid-19 pandemic.

Furthermore, we conjecture that the combined adoption of the previous two actions (i.e., acting on prices and defining the level of flexibility of the reservation) should be considered as a separate specific marketing choice that allows the host to extract a higher rent through price discrimination [37] amongst the emerging market segments resulting from the Covid-19 pandemic outbreak. In this sense, unobserved '*high type*' travelers (e.g., high-level 'business travelers') – who are less price sensitive – are sorted, through a self-selection mechanism, which is associated with a need for a higher schedule flexibility.

In line with these premises, we expect to observe the following outcomes on the Airbnb market as a consequence of the Covid-19 outbreak. First, we expect Airbnb hosts to respond with more prominent marketing activism than in the pre-pandemic situation, which can be translated into the following hypotheses:

HP1a: Following the emergence of the pandemic shock, we expect a significant response in the pricing adjustments of Airbnb hosts, in terms of an increased magnitude of price adjustments, with respect to their activity in the years before the Covid-19 outbreak.
HP1b: Following the emergence of the pandemic shock, we expect a significant response in the marketing choices of Airbnb hosts, in terms of an increased adoption of flexible reservation procedures.

Second, we ponder whether greater activism is associated with rational expectations, i.e., whether the choice of adopters of the new marketing mix is rewarded by higher economic returns. To this end, we argue that Covid-19, rather than resulting in a uniformly diffused negative demand shock [15], has significantly changed the preferences of Airbnb customers (as in [12], on different variables). Indeed, as stated above, the unpredictability of medium-term forecasts on the spread of the Covid-19 pandemic has made customers more sensitive to the level of service flexibility offered by Airbnb hosts. In fact, during the Covid-19 shock, the likelihood of withdrawing a reservation, even just a few days before an overnight stay, was significantly higher compared to that in the pre-pandemic conditions. Therefore, we formulate the following hypotheses:

HP2a: Following the emergence of the pandemic shock, we expect that, on average, hosts that switch to flexible cancellation policies obtain better occupancy rates than hosts that maintain a strict cancellation policy.
HP2b: Following the emergence of the pandemic shock, we expect that, on average, hosts that switch to flexible cancellation policies obtain higher revenues per available night than hosts that maintain a strict cancellation policy.

Third, the combined use of flexible cancellation policies and price adjustments may allow hosts to exploit profitable self-selection mechanisms [34], i.e., the joint use of the two marketing choices should be super-additive. In particular, following the emergence of the new customers' needs associated with the Covid-19 outbreak, hosts can sort less price sensitive customers (e.g., business travelers and/or travelers who place higher value on the flexibility of services) from more sensitive ones, and offer flexible policies together with higher prices. In line with these arguments, we formulate the following hypotheses:

HP3a: Following the emergence of the pandemic shock, we expect that the joint adoption of flexible cancellation policies and price increases the occupation rate.
HP3b: Following the emergence of the pandemic shock, we expect that the joint adoption of flexible cancellation policies and price increases the revenues.

4. Data and methodologies

4.1. Data description

The empirical setting of the study is the city of Rome, which is rather interesting for several reasons: i) it is one of the most important touristic locations in the whole global touristic industry, ii) it represents the largest Airbnb market in Italy, when considering the number of properties [38], and iii) it attracts a wide variety of tourists, and welcomes not only leisure and business travelers, but also those from other micro-segments (e.g., religious).

We gathered the data employed in the empirical analyses from AirDNA, a leading worldwide provider of short-term rental data (https://www.airdna.co). Our data are composed of a monthly panel dataset of 10,498 Airbnb properties located in the city of Rome that were active for at least one day in 2018, 2019, and 2020.[3] We have chosen this sample definition for two main reasons: a) to analyse how changes in the marketing choices of Airbnb hosts, in response to a shock, influenced the economic returns, and b) to provide a benchmark that could be used to assess the phenomenon of the diffusion of new marketing choices in the presence of the pandemic shock, compared to the frequency of marketing choice adjustments in 'common' years (i.e., 2018 to 2019), albeit characterised by the well-known growth of the short-term accommodation market. To this aim, it has been necessary to observe the same properties before (i.e., in 2018 and 2019) and after (i.e., in 2020) the pandemic outbreak, in order to compare hosts that adopted new marketing choices year-over-year and those who continued with the same ones, in either a shocked year or a non-shocked one.

In our empirical analysis, the time frame we considered to be affected by the Covid-19 pandemic is the interval between March and December 2020 (as reported by [18]).

4.2. Variable operationalization

4.2.1. Dependant variables: occupation rate and revenues

We studied the impact of a specific set of marketing choices on the economic returns and revenues listing, assuming that each property-owner made his/her marketing choices to maximize their economic returns. We proposed two proxies for these returns, according to the main operationalizations presented in the literature: the ability of the host to capture the demand in the area, and the corresponding revenues generated by such individual demand, that is, the occupancy rate (OccR) and the revenues per active nights (RevPAN).

Occupation rate (OccR) is the number of nights reserved in a month, normalized by the number of active nights[4] in the same month. This indicator depends on the exogenous demand for accommodation in the specific area where the property is located, the price, the position in the area, and the quality of the accommodation (including the quality of the associated services). This variable is the non-monetary performance measure that is usually adopted in the Airbnb literature (see, amongst others, [39]).

Revenues per active nights (RevPAN) is the total revenues collected in the month, normalized by the number of active nights[5] in the same month. The indicator depends on the occupation rate and the unit margin. RevPAN is a good proxy for variable earnings, because Airbnb does not charge any fixed fee for being active, and the transaction fee is linearly proportional to the revenues (3%−6% of the host's revenues). This metric is frequently used in the econometric analyses of touristic performances [40] and, with specific reference to our case study, it has frequently been adopted in performance evaluations of Airbnbs [17].

With the aim of describing the impact of the shock in our sample, Table 2 reports the descriptive statistics of the two dependant variables for the considered three years, that is, 2018, 2019, and 2020. In line with

[3] The choice of using continuously active listings over multiple time-periods has already been made in the Airbnb literature employing AirDNA data. See, for instance, Gunter et al. (2020), who examined listing-level demands within the city of New York.

[4] Airbnb hosts, after their registration on the platform, can decide, on a day-to-day basis, whether to make an individual property available for booking or to block it. An 'active night' is a specific date on which the property is present on the Airbnb site and is not blocked. Normalizing reservations by active nights allows a comparison to be made of the economic returns of properties that are differently available on the platform.

[5] See footnote iii.

Table 2
Descriptive statistics for occupation rate and revenues per active night within the universe of continuously active listings.

		Mean	Std. Dev.	Min	Max
Occupation Rate	2018	51.09%	37.52%	0.00%	100.00%
	2019	55.11%	37.24%	0.00%	100.00%
	2020	17.77%	29.71%	0.00%	100.00%
Revenues per Active Night	2018	\$ 61.83	\$ 74.26	\$ 0.00	\$ 1,554.25
	2019	\$ 65.86	\$ 79.52	\$ 0.00	\$ 2,614.20
	2020	\$ 14.47	\$ 48.15	\$ 0.00	\$ 3,136.20

Note: a) Source: The authors' calculations of AirDNA data. b) Sample: 10,498 Airbnb listings (see the introduction to Section 4). c) Observation Period: March-December of each year. This period was chosen to compare shock situations (i.e., March-December 2020, as in [18]) with common ones (i.e., March-December 2018 and 2019).

Ghebreyesus [18], the descriptive statistics are computed for the months of March to Decemeber of each year. Consistent with the magnitude of the shock, Table 2 reports that the mean values of occupation rate and revenues per active nights declined significantly in 2020, compared to 2018 and 2019, years that were instead rather stable.

4.2.2. Explanatory variables: marketing choices employed by Airbnb hosts

In line with our hypotheses, we examined the marketing decisions surveyed in our database that may have been used by Airbnb hosts in response to the epidemic. Specifically, we examined both price adjustment decisions and choices to adapt the functional attributes of the service (cancellation policies, Instantbook option, the switch to medium-term rentals,[6] and the requirement of a security deposit). Regarding the latter, we then decided to focus our attention on cancellation policies, which proved to be the most impactful service offered to Airbnb customers. This choice is also justified by the adoption rates of the other marketing choices made by Airbnb hosts when facing Covid-19, since they may not have been adopted (medium-term rentals and security deposit), or may have had an ambiguous correlation with the shock (Instantbook).[7]

Price adjustments. This variable was used to identify the price adjustment induced by the pandemic shock. To this aim, we decided to measure the year-over-year price variation of each property-month observation to calculate the listing-level price trends. We started by measuring the mean posted price for each listing, *i,* in a month, *m,* of a given year, *y* ($y = 2018$, 2019, and 2020; *m* from January to December), namely *Price(i,m-y)*.[8]

We then measured $PV^{y}_{(i,m)}$ as the percentual price variation of listing *i* in month *m,* with respect to the same month in the previous year ($y =$ 2019 and 2020):

$$\mathbf{PV}^{\mathbf{y}}_{(\mathbf{i,m})} = \mathbf{Price}_{(\mathbf{i,m-y})} / \mathbf{Price}_{(\mathbf{i,m-(y-1)})} - \mathbf{1} \tag{1}$$

In this study, we have used $PV^{2020}_{(i,m)}$ (*m* from March to December) as a proxy for the price choices adopted in correspondence to the Covid-19 pandemic shock. This price change (i.e., the average price of the property in one month between March and December in 2020, with respect to the average price of the same property in the same month in 2019) could also have been driven by other events during the year, but we believe that the effect of the shock would have been much larger than the *average* effects of other events in determining the observed price trends. On the other hand, the yearly horizon of the price adjustment, *PV,* guarantees that the relevant seasonality of the prices was taken into consideration correctly.

Cancellation policies. Following the Covid-19 outbreak, one of the most evident problems of travelling was connected to the fact that the risk of cancelling the reservation a few days before the stay was very high. Therefore, we considered the specific cancellation policies adopted in each year for each property. According to Airbnb, a property, *i,* can provide three different cancellation policies: *Strict* (a total reimbursement is only granted within 30 days before the overnight stay), *Moderate* (reservations can be withdrawn with no additional costs up to 5 days before the first overnights stay), and *Flexible* (reservations can be withdrawn with no additional costs up to 24 h before the overnights stay).[9] In line with this classification, we defined a dummy variable, $ModFlexPolicy_{i,year}$, equal to one if property *i* in a given year *y* ($y = 2018$, 2019, 2020) granted Moderate or Flexible terms, and equal to zero otherwise. We made this decision after considering that the definition of the two policies, Moderate and Flexible, is such that they may appear quite similar to the average Airbnb customer, and quite different from the rigid policy. Indeed, coverage from (travel) uncertainties up to 5 days or 1 day before the stay makes little difference with respect to the need to make a final decision (when the policy is strict) 30 days before.[10] However, in order to ensure that our estimates were robust regarding this classification, we ran multiple robustness checks, the results of which are presented in Section 5.2.

Finally, it is worth noting that our data source records this information once a year (on 31st December). As a consequence, in the following econometric analyses, we measured the change in cancellation policy as a result of the shock since the cancellation policy as of 31/12/2020 has changed from the latest recorded information on cancellation policy as of 31/12/2019 (i.e. well before the official start of the pandemic in March 2020; [18]). We can therefore be confident that our variable incorporates the effects of the shock.

4.2.3. Control variables

We controlled for different confounding factors that could affect the outcome of the economic returns of the properties. First, we controlled for neighbourhood fixed effects, as the location of properties within a city generally has a significant impact on prices and performances [41]. Second, we controlled for the structural characteristics of the listings, such as the listing type (i.e., including a dummy variable equal to one if the listing was a room, shared or private, and 0 if it was an entire

[6] In other words, requiring stays that last at least 28 days, or more.

[7] Comparing the distributions of the adoption rates of cancellation policies and Instantbook, it is possible to notice that, although there is a unique direction toward moderate and flexible policies (i.e., very few hosts, 1%, decided to switch from moderate/flexible terms to stricter ones) in the former marketing choice, the choice of Instantbook is in both directions, since the number of hosts that switched to Instantbook in 2020 (7%) is similar to those who decided to eliminate Instantbook (9%).

[8] We computed the mean value of these prices over a month, m-year, considering each day in which property i was active.

[9] Further information can be found on: https://www.airbnb.com/help/article/475.

[10] It is worth noting that the shift from rigid to flexible (or moderate) cancellation policies introduces an opportunity cost that is proportional to the probability that a given customer withdraws his or her reservation and a new customer cannot be found in place of the previous one. To provide a first order of magnitude of these costs in the pre-Covid era, we calculated the average price changes from 2018 to 2019 for properties adopting strict terms in 2018 and moderate/flexible terms in 2019. In line with expectations, we found an average price increase of 1.3%, which is a plausible upper bound for the opportunity cost we are considering. We expect the cost of offering more flexibility to customers during the pandemic - when travel uncertainty was the highest - to have increased significantly. However, as mentioned, these costs are opportunity costs, so that comparing revenues as proxies for profits even after the introduction of flexible policies does not introduce any relevant bias. We would like to thank an anonymous reviewer for suggesting clarifying this aspect.

apartment[11]) and the number of beds (log-transformed), as suggested by various authors [35,41,42]. Third, we controlled for signals that play an important role on P2P markets and have a significant impact on performances [28,42,43]. Thus, we included the following variables as controls: the presence of a superhost badge, by the means of a specific dummy variable (equal to one if the host was a superhost, and equal to zero otherwise), the number of reviews and photos (both log-transformed), and the overall rating. Fourth, we controlled for the presence, or not, of instant-booking [44], which can be considered as an alternative marketing lever in the hands of hosts, by the means of a specific dummy variable equal to one if the property included the Instantbook option. Finally, we included month-of-the-year fixed effects to account for seasonal effects and neighbourhood multiplied by month-of-the-year fixed effect to account for any unobserved shocks at a certain point in time in a given neighbourhood.

4.3. Econometric approach

The data were tested with the following econometric model:

$$\mathrm{Y}(\mathbf{i},\mathbf{m}) = \mathbf{a} + \mathbf{b_1}\ \mathbf{PV}^{2020}_{(\mathbf{i},\mathbf{m})} + \mathbf{b_2}\ \mathbf{ModFlexPolicy}_{(\mathbf{i})} + \mathbf{b_3}\ \mathbf{PV}^{2020}_{(\mathbf{i},\mathbf{m})} * \mathbf{ModFlexPolicy}_{(\mathbf{i})} + \mathbf{X}_{(\mathbf{i})} + \mathbf{M}_{(\mathbf{t})} + \varepsilon_{(\mathbf{i},\mathbf{t})} \tag{2}$$

where *Y (i,m)* is either the *OccR* or the *RevPAN* in month *m* (*m* = March … December) in the year 2020, while $PV^{2020}_{(i,m)}$ and $ModFlexPolicy_{(i)}$ are the variables that represent the marketing choices adopted at the listing level, and $X_{(i)}$ and $M_{(t)}$ are the control variables expressed in Sections 4.2.2 and 4.2.3. In order to analyse the incidence and the effects of service flexibility choices in response to the Covid-19 shock, Eq. (2) was tested on a sub-sample, selected from the universe of the 10,498 properties (i.e., see Section 4.1) of those listings that adopted a *Strict* cancellation policy in 2019. As reported below (see Section 5.1), these are 4497 listings. It is worth noting that, on the basis of the selection of this sub-sample, the β_2 coefficient has to be interpreted as the elasticity of the economic returns on the basis of the *adoption* of moderate/flexible cancellation policies in 2020, compared to listings that continued to have strict policies from 2019. In this vein, β_2 is of interest for both *HP2a* and *HP2b*. Moreover, the β_3 coefficient is of interest for *HP3a* and *HP3b,* as it measures the moderating effects of marketing choices on the price elasticity of the demand and economic returns.

[11] The delay between reservation and overnight stay is, on average, much longer than the 1/5 days of the flexible/moderate policies. In fact, in our universe of hosts, the average delay is 29.4 days for reservations made for March-December 2020. In this sense, almost all of the uncertainty between the booking and the stay is borne by the host in the case of flexible or moderate policies, while a very significant part of the uncertainty is borne by the visitor through a rigid policy, and this evidence supports our choice to treat moderate and flexible policies as a single 'non-strict' policy. However, it should be noted that the average delay in bookings for the March-December 2020 period was significantly reduced, compared to bookings for the March-December 2019 period (from 42.8 days to 29.4 days; see the evidence in Table A3 in the Online Appendix). This confirms the changed behavior of tourists following the Covid-19 pandemic shock and the hypothesis of the emergence of the new needs of customers that can be profitably addressed by hosts through appropriate screening strategies. However, if the average delay becomes too small, the differences between moderate and flexible policies might be significant, and treating them as equal policies might then be inappropriate. This is why we conducted several robustness checks to see whether moderate and flexible policies identify different tactics with different objectives/effects: however, all the conducted checks supported our choice to treat moderate and flexible policies as not being significantly different. We would like to thank the anonymous reviewer for this suggestion.

Table A1 in the Online Appendix provides the descriptive statistics of the variables employed in the econometric models (dependant, independent, and control variables). Table A2 in the Online Appendix instead provides the correlation matrix, which shows that no strong correlations were likely to emerge between our regressors.

4.3.1. Endogeneity issues

4.3.1.1. (Un)Observed listing quality. The economic returns of the Airbnb listings, as well as the main explanatory variables (price adjustments and flexible cancellation policies) may be correlated with some unobservable characteristics that vary between listings (e.g., the quality features of the property), and may thus be absorbed in the cross-sectional error term. In order to deal with these omitted variables, we took advantage of the conservative assumption, previously formulated by Farronato & Fradkin [40] and Gunter et al. [29], whereby higher unobservable quality is reflected in higher prices. According to this assumption, and using the algorithm proposed by Farronato & Fradkin [40], we estimated the qualitative heterogeneity within the listings from the distribution of the average prices in 2018, without needing to deal with the specific characteristics that were not directly observable in our datasets. The resulting $UnobservedListingQuality_{(i)}$, which is a continuous variable with a zero mean and is almost normally distributed (as reported in the descriptive statistics in Table A1 in the Online Appendix), was included in the set of control variables.

The variable was computed as follows: i) we first defined the $AveragePricePerGuest_{i,\text{m-2018}}$ variable, which is the average nightly price, $Price_{(i,\text{m-2018})}$ (see Section 4.2.2), normalized by the number of beds, ii) we then normalized the $AveragePricePerGuest_{i,\text{m-2018}}$ variable over its average value in the corresponding neighbourhood in order to minimize any spatial-autocorrelation concerns, thus defining the $AveragePricePerGuest\_NeighNorm_{i,\text{m-2018}}$ variable, and iii) we ran a panel data regression to estimate the $AveragePricePerGuest\_NeighNorm_{i,\text{m-2018}}$ log (in 2018) over the time trend, the month of the year fixed effects, and the listing-level individual fixed effects. Finally, we computed the individual fixed effects and applied empirical Bayes shrinkage to minimize any biases in the analyses. Fig. 1 provides the distribution of the resulting $UnobservedListingQuality_{(i)}$ variable.

The definition and inclusion of this variable in the control set offered certain advantages. First, since it was estimated on the price distribution in 2018, which is not included in the estimation samples of the subsequent analyses, it did not result in any co-determination issues, and it considered prices in a stationary situation (i.e., not impacted by the Covid-19 pandemic). Second, it allowed us to control for any correlation between marketing choices and unobserved variables that could have biased the coefficients of the analysis. This variable also controls for any amenities (which were not observed in our data) that may have had specific (differential) effects before and after the pandemic, and which could thus have biased our analysis.

4.3.1.2. Endogeneity of price adjustments. In order to deal with the endogeneity of the price adjustments that explained the occupation rate and revenues per active nights, we identified an appropriate instrumental variable for $PV^{2020}_{(i,m)}$. It is likely that, following the operationalization of $PV^{2020}_{(i,m)}$, which depends on the price posted at the time of the reservations, co-determination issues could have arisen, given that price and demand are simultaneously determined in a traditional economic setting. For this reason, we had to identify a variable that was correlated with the pricing decision of listing *i* at time *m-y*, but uncorrelated with its

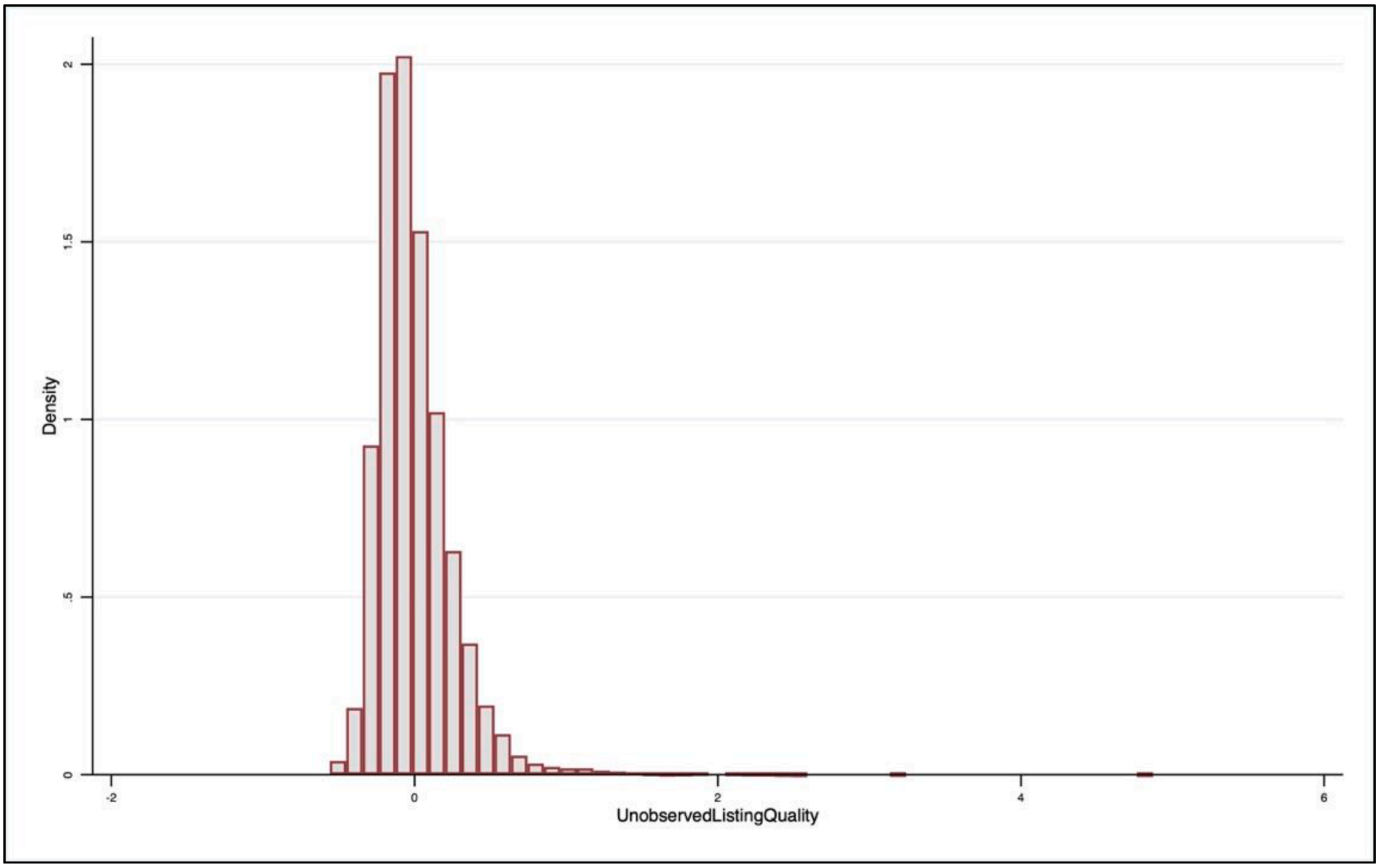

Fig. 1. Distribution of the UnobservedListingQuality$_{(i)}$.

occupation rate or revenues per active nights.

We therefore identified the *AVG PV Neigh*$_{(i,m)}$ variable as effective instrumental variable for $PV^{2020}_{(i,m)}$. The variable was computed as the average $PV^{2020}_{(i,m)}$ of the listings in the same neighbourhood as listing *i*, but excluding listing *i*.[12] In this sense, the variable was likely to directly affect the pricing adjustments of listing *i*, and, consequently, its demand and economic returns, because of a strategic interaction (i.e., price mimicking; [45]), or because of centralized suggestions from the platform.[13] These arguments were also likely to hold since our model controlled for unobserved quality characteristics at the listing level and specific shocks at the neighbourhood level at a certain point in time. The validity of the instrument (which is significantly correlated with the endogenous $PV^{2020}_{(i,m)}$ variable) is discussed in the next section by means of statistical tests, such as the Kleibergen-Paap weak instrument statistic test [46].

5. Results

5.1. Marketing choices and the Covid-19 outbreak

This section provides multiple statistical comparisons of both the pricing activism (i.e., $PV^{2020}_{(i,m)}$) and the cancellation policy choices (i.e., *ModFlexPolicy*$_{(i)}$), and compares the transitions between 2018 and 2019 (i.e., a stationary situation) and between 2019 and 2020 (a shock impacted situation). The objective of these comparisons was to test the overall variation in pricing adjustments, and the differences in the adoption of moderate/flexible cancellation policies in order to verify whether the Covid pandemic shock has actually enhanced marketing activism within the Airbnb population, compared to a benchmark situation.

Table 3
Cancellation policy distribution. Sample: 10,498 listings (i.e., full sample, see the introduction in Section 4).

a. Benchmark Situation: 2018 and 2019	CP 2019: Flexible	CP 2019: Moderate	CP 2019: Strict	TOT (2018)
CP 2018: Flexible	5,949 (56.67%)	0 (0.00%)	109 (1.04%)	**6,058 (57.71%)**
CP 2018: Moderate	3 (0.03%)	30 (0.29%)	5 (0.05%)	**38 (0.36%)**
CP 2018: Strict	19 (0.18%)	0 (0.00%)	4,383 (41.75%)	**4,402 (41.93%)**
TOT (2019)	**5,971 (56.88%)**	**30 (0.29%)**	**4,497 (42.84%)**	**10,498 (100.00%)**
b. Shock Situation: 2019 and 2020	**CP 2020: Flexible**	**CP 2020: Moderate**	**CP 2020: Strict**	**TOT (2019)**
CP 2019: Flexible	5,571 (53.07%)	295 (2.81%)	105 (1.00%)	**5,971 (56.88%)**
CP 2019: Moderate	2 (0.02%)	26 (0.25%)	2 (0.02%)	**30 (0.29%)**
CP 2019: Strict	554 (5.28%)	445 (4.33%)	3,488 (33.23%)	**4,497 (42.84%)**
TOT (2020)	**6,127 (58.36%)**	**776 (7.39%)**	**3,595 (34.24%)**	**10,498 (100.00%)**

Table 3 provides the number of properties (and the relative shares in brackets) that adopted a given cancellation policy (moderate, flexible, or

[12] The descriptive statistics of the variable are available in Table A1 in the Online Appendix.

[13] See, for instance, the following press article by Forbes: https://www.forbes.com/sites/ellenhuet/2015/06/05/how-airbnb-uses-big-data-and-machine-learning-to-guide-hosts-to-the-perfect-price/

Table 4
Absolute variations in the prices. Shock situation (column (a), March-December 2020 vs March-December 2019) and benchmark situation (column (b), March-December 2019 vs March-December 2018).

	Absolute price variations 2020 vs. 2019 $\|PV^{2020}\|$ (a) Sample: 4497 Airbnb properties that adopted *Strict* policies in 2019	Absolute price variations 2019 vs. 2018 $\|PV^{2019}\|$ (b) Sample: 4442 Airbnb properties that adopted *Strict* policies in 2018	Absolute price variations 2020 vs. 2019 $\|PV^{2020}\|$ (a) Sample: the universe of 10,498 Airbnb properties	Absolute price variations 2019 vs. 2018 $\|PV^{2019}\|$ (b) Sample: the universe of 10,498 Airbnb properties
Mean	0.176	0.121	0.157	0.121
Std. Dev	0.193	0.127	0.189	0.134
Min	0.000	0.000	0.000	0.000
25th Perc.	0.046	0.040	0.037	0.039
Median	0.100	0.081	0.081	0.075
75th Perc.	0.256	0.158	0.216	0.152
90th Perc.	0.438	0.277	0.404	0.278
99th Perc.	0.927	0.639	0.920	0.686
T-Stat (Mean Comparison)	48.571***		49.296***	
P-Val (Mean Comparison)	0.000		0.000	

Note: a) Descriptive statistics for the absolute value of $PV^{2020}_{(i,m)}$ and $PV^{2019}_{(i,m)}$ are displayed. The absolute value was chosen since the purpose of the table is to show the magnitude of the price variations rather then their direction. b) First two columns: Column on the left: 4497 Airbnb listings employing strict policies in 2019, and observed in March-December 2020 (chosen according to [18], to analyse the effects of Covid-19); Column on the right: 4442 Airbnb listings employing strict policies in 2018, and observed in March-December 2019 (chosen according to [18], to act as a benchmark situation). c) Last two columns: Column on the left: universe of 10,498 Airbnb listings observed in March-December 2020 (chosen according to [18], to analyse the effects of Covid-19); Column on the right: universe of 10,498 Airbnb listings observed in March-December 2019 (chosen according to [18], to act as a benchmark situation). d) The T-Stat (Mean Comparison) compares the mean value in 2020 with that of 2019, and tests whether the former is significantly larger than the latter. e) *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; + $p < 0.10$.

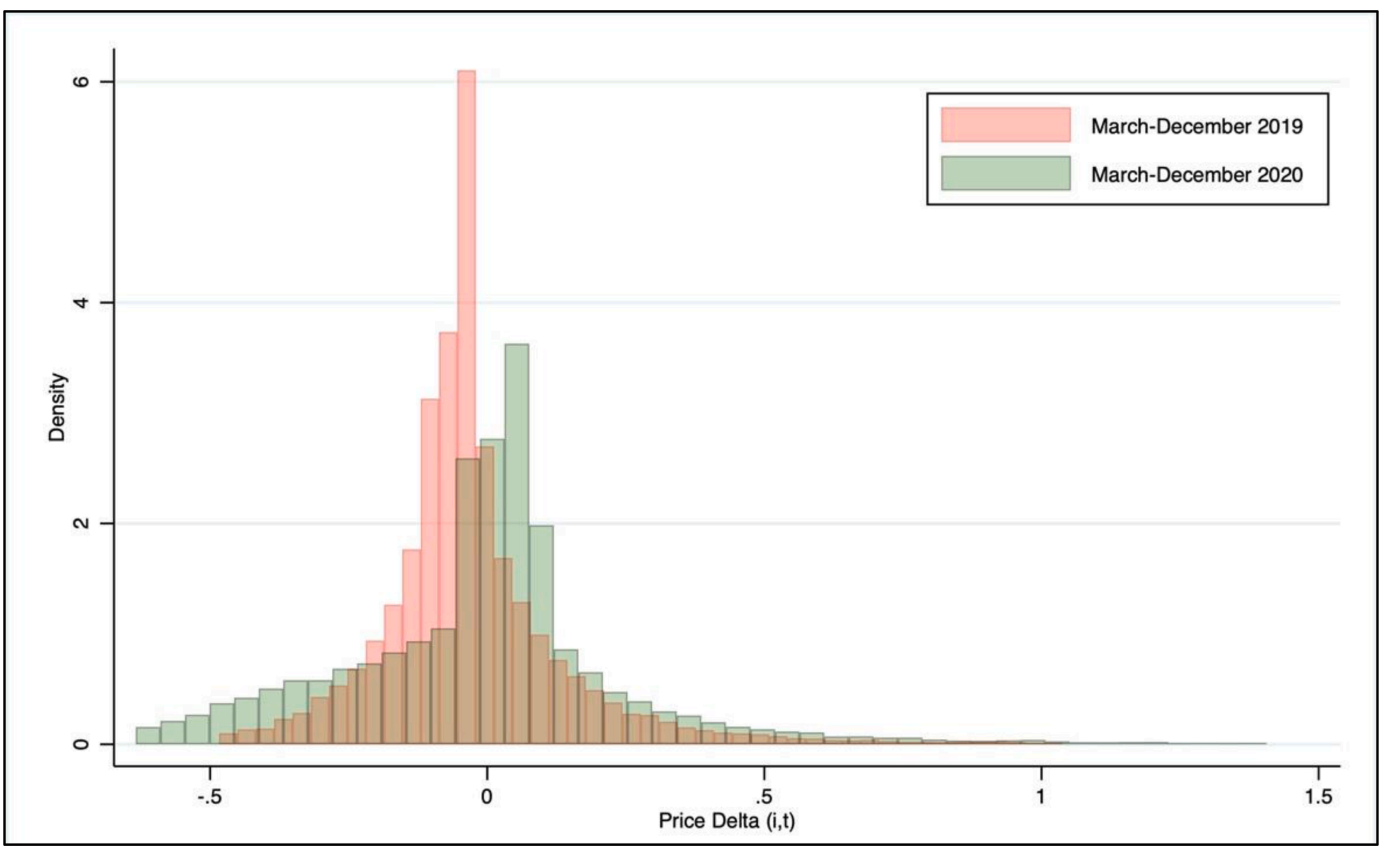

Fig. 2. Distribution of $PV^{y}_{(i,m)}$. Shock situation (column on the left, March-December 2020) vs benchmark situation (column on the right, March-December 2019). Note: a) Histogram of the values of $PV^{2020}_{(i,m)}$ and $PV^{2019}_{(i,m)}$ are displayed. b) Green Bars: 4497 Airbnb listings that employed strict policies in 2019, and observed in March-December 2020 (chosen according to [18], to analyse the effects of Covid-19). c) Red Bars: 4442 Airbnb listings that employed strict policies in 2018, and observed in March-December 2019 (chosen according to [18], to act as a benchmark situation) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

strict) in 2018, 2019, and 2020, and also shows the year-over-year transitions. Table 3a shows data pertaining to the benchmark situation (i.e., 2018 to 2019), while Table 3b shows data for the Covid-19 shocked situation (i.e., 2019 to 2020). Table 4 provides a comparison of the pricing adjustements between 2018 and 2019 and between 2019 and 2020, and it also shows the main descriptive indicators for the *absolute* price variation (i.e., the absolute value of $PV_{(i,m)}$) as well as the results of a mean comparison test (i.e., the T-test). Fig. 2, which is complementary to Table 4, plots the distribution of $PV^{y}_{(i,m)}$ in 2019 and in 2020.

Tables 3a and 3b indicate that, passing from 2019 to 2020, there was a significant increase in the activism of hosts with regard to their marketing choice propositions involving the level of service: only 136 hosts (1.30%) modified their cancellation policy during 2019, compared to the offering in 2018, while 1413 hosts (13.46%) did so during 2020. A total of 1009 Airbnb properties (9.61%, most of the 1413 properties that changed their policy; or 22.7% of the hosts who adopted strict policies in 2019) abandoned the strict policies in favour of flexible or moderate ones. Second, Table 4, which refers to the year-over-year price variations, shows that a significant difference is likely to exist between the price-variation adjustments adopted when comparing the transitions from 2018 to 2019 and from 2019 to 2020, as the absolute price variation is significantly higher in the presence of a shock. Indeed, the mean values and the corresponding T-tests confirm that: i) when passing from 2019 to 2020, the hosts were more inclined to act on prices than in the passage between 2018 and 2019, ii) this variation is more evident at the extremes of the distribution, as can be seen from the 75th, 90th, and 99th percentiles in Table 4. Fig. 2 confirms these arguments, as it can be noted that both tails of the distribution of $PV^{2020}_{(i,m)}$ are clearly more pronounced than the tails of the distribution of $PV^{2019}_{(i,m)}$.[14]

We have interpreted these results as indicating the presence of enhanced activism in the transition between 2019 and 2020 (in the presence of the Covid-19 pandemic shock), compared to the transition between 2018 and 2019 (the pre-Covid situation). In other words, a larger proportion of properties reacted to the pandemic with either more marked upward or downward variations in prices (thus confirming the qualitative guesses of [13]), or with variations in their cancellation policies, thus confirming the arguments that support *HP1a*. Indeed, as reported in Table A3 in the Online Appendix, which provides more detailed information on the demand side customer segments, the heterogeneity of the new needs of customers during the Covid-19 pandemic, in terms of reservation timing, has clearly emerged (i.e., the last-minute demand share increased sharply, and this figure represents more than half of the reservations made on the entire Roman market in 2020). We can therefore interpret this enhanced activism as a marketing response of Airbnb hosts to the emerging (and new) segmentation of customers.

5.2. Econometric analyses: marketing choices and economic returns

This section shows the results of the econometric estimations that were conducted to show how the observed economic returns (i.e., *OccR* and *RevPAN*) varied in relation to the adopted marketing choice. Given the nature of our analysis, and considering that the data on service policies are only observed once per year, we estimated the econometric models with 2SLS by taking advantage of the *Unobserved Listing Quality* variable to control for any time-invariant omitted variables and by using an appropriate IV to deal with the endogeneity of $PV^{2020}_{(i,m)}$. Furthermore, all models employ robust to heteroskedasticity standard errors. The observations were winsorized at the 1st and 99th percentiles of the within-sample distribution of the $PV^{2020}_{(i,m)}$ variable in order to avoid *extreme* price adjustments, which may be the consequence of incorrect data or may be associated with properties that experienced dramatical changes from one year to the other.[15] As reported in Section 4.3, the estimates referred to the sample of strict cancellation policy adopters in 2019, and comparisons were made with the sample of strict cancellation policy adopters in 2018 to infer any changes, compared with the pre-Covid situation (these comparisons are all available in the Online Appendix).

5.2.1. The impact of marketing choices on the occupation rate

Table 5 shows the estimates of the econometric model that was used to predict the impact of the pricing adjustments, the impact of the flexible cancellation policies, and the effect of joint adoptions on the occupation rate. It is worth noting that the IV diagnostic statistics (i.e., Kleibergen-Paap weak identification tests) fully confirmed the validity of the instrument for our empirical setting.[16] Models M1 and M2 include control variables only, Model M3 includes control variables and $PV^{2020}_{(i,m)}$, Model M4 includes control variables and $ModFlexPolicy_{(i)}$, Model M5 includes control variables, $PV^{2020}_{(i,m)}$, and $ModFlexPolicy_{(i)}$, while Model M6 includes all the variables as well as the interaction between $PV^{2020}_{(i,m)}$ and $ModFlexPolicy_{(i)}$. Table A4 in the Online Appendix provides the estimation results when a pooled OLS estimation was employed, without instrumenting $PV^{2020}_{(i,m)}$, and rather similar results can be observed.

Two main results emerge from Table 5. First, as expected, the price variations are negatively and significantly correlated with the occupation rate (i.e., the higher the price is, the lower the demand): in particular, we can see that, on average, when all the other variables are held constant, a 10% increase in $PV^{2020}_{(i,m)}$ is associated with a 1.27 percentage point (pp) decrease in *OccR* (model M5). Second, it can be noted that the listings that adopted a moderate/flexible cancellation policy in 2020, on average have a higher occupation rate than those that maintained stricter cancellation policies (with this difference being significant at the 99.9% confidence level), thus confirming *HP2a*. The magnitude of these coefficients should be interpreted by considering that the average *OccR* in the estimation sample is 18.02%, so that the effect of the adoption of *Moderate/Flexible* policies alone – from 4.7pp (model M5) to 5.6pp (model M4) – results in a significantly marked impact that is about a third of the within sample mean value of *OccR*.

The interacted effect is positive and significant at the 99% confidence level, thus showing that the effects of the two marketing choices under examination are not linearly separable, i.e., their combination seems to be effective in sorting customers with different demands to price elasticity. M6 predicts that the price elasticity in the segment of properties that adopted a flexible policy is almost zero.[17] In line with *HP3a*

[14] This result was confirmed at a 99% confidence level by means of a Kolmogorov-Smirnov test.

[15] For the sake of completeness, the following data were dropped from the estimation: a) The observations in the highest percentile (after 99th perc.), because they showed a mean value of PV2020 around +2000%, and a standard deviation around +3400%, denoting observations in which the value of PV2020 varied between +144% and around +29300%. b) The observations in the lowest percentile (before the 1st percentile), because they showed a mean value of PV2020 around −69%, and a standard deviation around 10.5%, denoting observations in which the value of PV2020 varied between values very close to −100% (highly unplausible) to −58%. As reported in the main text, we dropped these observations from the analyses for two main reasons. First, in many cases, the extreme values may have been typed in incorrectly. Second, whenever such extreme figures have not been mistyped, it is very likely that they are associated with properties that have drastically changed in nature (extraordinary maintenance, services offered), which could obscure the marketing choices that should be attributed to the pandemic shock.

[16] We tested our model on a classical OLS, without using any instrumental variable for PV2020(i,m). OLS predicted an upward biased estimate for models M4 and M5, while the downward OLS in model M6 estimated the elasticity of the Occupation Rate to PV2020(i,m) and led to a non-significant estimate of the interaction between PV2020(i,m) and the ModFlexPolicy(i) dummy. The obtained results are reported in Table A4 in the Online Appendix.

[17] We performed a statistical computation of the linear combination of β1 and β3, which showed an average value of 0.17, and values that varied between 0.06 and 0.29 at the 95% confidence level.

Table 5
The impact of marketing choices on the occupation rate. Observation period: March 2020 to December 2020. Estimation method: 2SLS. $Y =$ Occupation rate. Sample: 4,497 Airbnb properties that adopted *Strict* policies in 2019.

		M1	M2	M3	M4	M5	M6
Unobserved Quality			0.018*	0.009	0.005	−0.001	0.003
			(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Private/Shared Room [vs APT]			−0.025***	−0.023***	−0.022***	−0.020***	−0.020***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln Beds			0.023***	0.019***	0.018***	0.015**	0.019***
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Superhost = YES			0.032***	0.032***	0.033***	0.033***	0.036***
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ln Review			0.027***	0.024***	0.024***	0.022***	0.023***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln Photos			0.012***	0.014***	0.012***	0.014***	0.013***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Rating			0.006	0.006	0.004	0.004	0.001
			(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Instantbook = YES			0.084***	0.080***	0.078***	0.075***	0.073***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
PV				−0.134***		−0.127***	−0.247***
				(0.009)		(0.009)	(0.025)
Mod. Flex. Policy [vs Strict]	HP2a				0.056***	0.047***	0.075***
					(0.004)	(0.004)	(0.007)
PV * Mod. Flex. Policy	HP3a						0.422***
							(0.079)
Constant		0.189***	−0.068**	−0.060*	−0.059*	−0.054*	−0.048*
		(0.004)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
neighbourhood fe		no	yes	yes	yes	yes	yes
neighbourhood * month fe		no	yes	yes	yes	yes	yes
Month FE		yes	yes	yes	yes	yes	yes
Observations		31,428	30,295	30,295	30,295	30,295	30,295
R2		0.023	0.091	0.111	0.098	0.115	0.086
Adjusted R2		0.023	0.086	0.105	0.093	0.110	0.081
Uncentered R2				0.357		0.360	0.339
AIC		11,690.284	10,009.228	9366.976	9797.884	9224.924	10,186.915
BIC		11,773.839	11,406.776	10,772.842	11,203.751	10,639.110	11,609.419
Kleibergen-Paap Underid. Test				2093.572		2023.192	422.732
Cragg-Donald Weakid. Test				1263.180		1277.957	233.444
Kleibergen-Paap Weakid. Test				25,128.004		24,958.531	500.029

Notes: a) Y(i,t) = Occupation Rate of a property, *i*, observed in month *t*. The time frame spans from March 2020 to December 2020. b) The econometric model was tested on the sub-set of properties that adopted *Strict* cancellation policies in 2019. c) The PV variable was instrumented with AVG PV Neigh using a 2SLS estimator. d) Standard errors are clustered at the property level. e) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

(confirmed by our analyses), we interpret the result as the emergence of a screening mechanism that is determined by the joint adoption of *Moderate/Flexible* policies and pricing adjustments, which is able to sort customers with different demand to price elasticities.

With the purpose of verifying the validity of our results, we then computed several additional estimates. Tables A5 and A6 in the Online Appendix show the results of the same models tested on the OccR for the March-December 2019 period over the sample of strict policy adopters in 2018 in order to provide a comparison with a stationary situation. The results show that the adoption of *Moderate/Flexible* policies has no significant effect on OccR and, at the same time, no screening mechanism is likely to hold. Tables A7 and A8 in the Online Appendix show the estimate of the econometric model on the universe of the properties in 2020 (i.e., regardless of which policy was adopted in 2019). In this case, the coefficient associated with the $ModFlexPolicy_{(i)}$ dummy cannot be interpreted as the *adoption* of *Moderate/Flexible* policies, but rather as the *proposition* of those *Moderate/Flexible* policies compared with the properties that proposed stricter services. Consistent with the estimates in Tables A7 and A8, we noted that the proposition of these policies is associated with a 2.8pp to 3.2pp increase in the occupation rate, but no screening evidence emerges (the interaction term is positive, but statistically insignificant), i.e., we could argue that flexible policies before the Covid-19 pandemic shock were not adopted for market segmenting purposes.

5.2.2. *The impact of marketing choices on revenues per active nights (RevPAN)*

Table 6 shows the estimates of the econometric model when *RevPAN* in 2020 was considered as the dependant variable and tested on the sample of strict cancellation policy adopters in 2019. Again in this case, it is worth noticing that the Kleibergen-Paap weak identification tests fully confirmed the validity of the instrument for our empirical setting.[18] Models M1 to M6 are defined as in Section 5.2.1. As for the analyses on the OccR, Table A9 in the Online Appendix provides the estimation results obtained when employing a pooled OLS estimation without instrumenting $PV^{2020}_{(i,m)}$, and they show rather similar results.

The model shows an average positive effect of price variation on the revenues per available night.[19] Indeed, Table 6 shows that, on average, an increase of 10% in price is associated with a \$6.04 to \$7.07 increase in *RevPAN*, which is significant at the 99.9% significance level. This is not surprising, considering that rational entrepreneurs adjust their prices, either upward or downward, to maximize their revenues. As for the adoption of *Moderate/Flexible* policies for strict policy adopters in 2019,

[18] As was done for the occupation rate, we also tested our model on a classical OLS, without using an instrumental variable for PV2020(i,m). OLS predicted downward biased estimates for models M4 and M5, while, in model M6, the OLS and the IV regressions showed a non-significant impact of PV2020(i,m) on revenues. The obtained results are given in Table A9 in the Online Appendix.

[19] The evidence of (small) increases in revenues, associated with price increases, complements the qualitative guesses made in the survey of Farmaki et al. [13].

 Information & Management 60 (2023) 103857

Table 6
The impact of marketing choices on revenues per active nights. observation period: March 2020 to December 2020. Estimation method: 2SLS. Y = Revenues per active night. Sample: 4497 Airbnb properties that adopted *Strict* policies in 2019.

		M1	M2	M3	M4	M5	M6
Unobserved Quality			54.025***	54.426***	52.555***	52.917***	53.187***
			(2.462)	(2.475)	(2.457)	(2.465)	(2.458)
Private/Shared Room [vs APT]			5.155***	5.057***	5.500***	5.411***	5.449***
			(0.802)	(0.796)	(0.803)	(0.797)	(0.792)
ln Beds			40.829***	41.009***	40.313***	40.486***	40.726***
			(1.734)	(1.738)	(1.731)	(1.733)	(1.728)
Superhost = YES			7.915***	7.896***	8.005***	7.990***	8.157***
			(0.830)	(0.827)	(0.828)	(0.825)	(0.826)
ln Review			1.744***	1.869***	1.473***	1.599***	1.630***
			(0.256)	(0.260)	(0.255)	(0.258)	(0.258)
ln Photos			2.987***	2.871***	2.987***	2.852***	2.785***
			(0.583)	(0.583)	(0.582)	(0.583)	(0.583)
Rating			2.702***	2.736***	2.489**	2.513**	2.295**
			(0.774)	(0.772)	(0.770)	(0.768)	(0.772)
Instantbook = YES			11.398***	11.585***	10.671***	10.836***	10.689***
			(0.607)	(0.613)	(0.618)	(0.621)	(0.621)
PV				6.043***		7.073***	−0.415
				(1.753)		(1.764)	(4.549)
Mod. Flex. Policy [vs Strict]	HP2b				6.600***	7.086***	8.835***
					(0.775)	(0.781)	(1.159)
PV * Mod. Flex. Policy	HP3b						26.412+
							(14.818)
Constant		23.128***	−76.546***	−76.880***	−75.566***	−75.884***	−75.506***
		(0.889)	(4.788)	(4.779)	(4.768)	(4.758)	(4.750)
neighbourhood fe		no	yes	yes	yes	yes	yes
neighbourhood * month fe		no	yes	yes	yes	yes	yes
Month FE		yes	yes	yes	yes	yes	yes
Observations		31,428	30,295	30,295	30,295	30,295	30,295
R2		0.007	0.144	0.145	0.147	0.148	0.148
Adjusted R2		0.007	0.139	0.140	0.142	0.143	0.143
Uncentered R2		0.007	0.144	0.145	0.147	0.148	0.148
AIC		3.43e+05	3.25e+05	3.25e+05	3.25e+05	3.25e+05	3.25e+05
BIC		3.43e+05	3.27e+05	3.27e+05	3.27e+05	3.27e+05	3.27e+05
Kleibergen-Paap Underid. Test				2,093.572		2,023.192	422.732
Cragg-Donald Weakid. Test				1,263.180		1,277.957	233.444
Kleibergen-Paap Weakid. Test				25,128.004		24,958.531	500.029

Notes: a) Y(i,t) = RevPAN of a property, *i,* observed in month *t.* The time frame spans from March 2020 to December 2020. b) The econometric model was tested on the sub-set of properties that adopted *Strict* cancellation policies in 2019. c) The PV variable was instrumented with AVG PV Neigh using a 2SLS estimator. d) Standard errors are clustered at the property level. e) *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$.

this decision is associated with higher revenues, that is, in the range of \$6.60 to \$7.08 more per available night, thus confirming *HP2b*, with almost a third of the average *RevPAN* being about \$24.00 within the estimation sample.

Again in this case, the joint effect of price adjustments and the adoption of strict policies is significantly positive, thus confirming the screening hypothesis (HP3b). Interestingly, when the joint effect is considered, the price effect alone loses significance, which is in line with a rational exploitation of the elasticity of the demand by the hosts. Fig. 3 plots the predicted *RevPAN* for different levels of $PV^{2020}_{(i,m)}$. The figure confirms that when a strict policy is proposed, no specific price effect can be predicted, while the adoption of moderate/flexible cancellation policies has explicit screening purposes, i.e., to sustain price increases in the segments where the demand is more rigid.

We verified the validity of our results by running several additional estimates. Again, we tested the same models for the RevPAN in 2019 as the dependant variable over the sample of strict cancellation policy adopters in 2018 to obtain a comparison with the baseline results referring to a stationary situation. The obtained results are shown in Tables A10 and A11 in the Online Appendix, and they show that the adoption of moderate/flexible policies, as well as the interaction of price adjustments and cancellation policy adoption, do not have any significant effects on *RevPAN*, thus indicating that the effectiveness of screening strategies only emerges in correspondence to the effects on consumer preferences brought about by the pandemic shock. It should also be noted that the increases in $PV^{2019}_{(i,m)}$ are, on average, associated with corresponding revenue increases, while in 2020 this only holds true for properties that screened customers through marketing choices. Tables A12 and A13 in the Online Appendix show the results of the estimates of the econometric model on the universe of properties in 2020 (i.e., regardless of which policy was adopted in 2019). The model confirms the results of the main model shown in Table 6.

5.2.3. Robustness checks

We conducted two additional robustness checks to validate our main estimation results for different operationalizations of the independent and control variables.

First, although *Section 4.2.2* shows that there are valid reasons to believe that flexible and moderate cancellation policies can be jointly merged in a single variable, we estimated our main models by treating the two policies separately. Tables A14 and A15 in the Online Appenidx provide the results that were obtained by estimating OccR and RevPAN, respectively, as dependant variables. In line with the main models, these robustness checks considered the Airbnbs that proposed a strict cancellation policy in 2019, and observed them between March and December 2020. Table A14 and Table A15 both use strict policies as the reference category upon which to understand the effects of moderate or flexbile ones. The estimations show that the results of the elasticity of economic returns on the adoption of moderate and flexible policies are somewhat comparable, for both OccR and RevPAN. Furthermore, we did not find any significant difference in the interacted effect of moderate

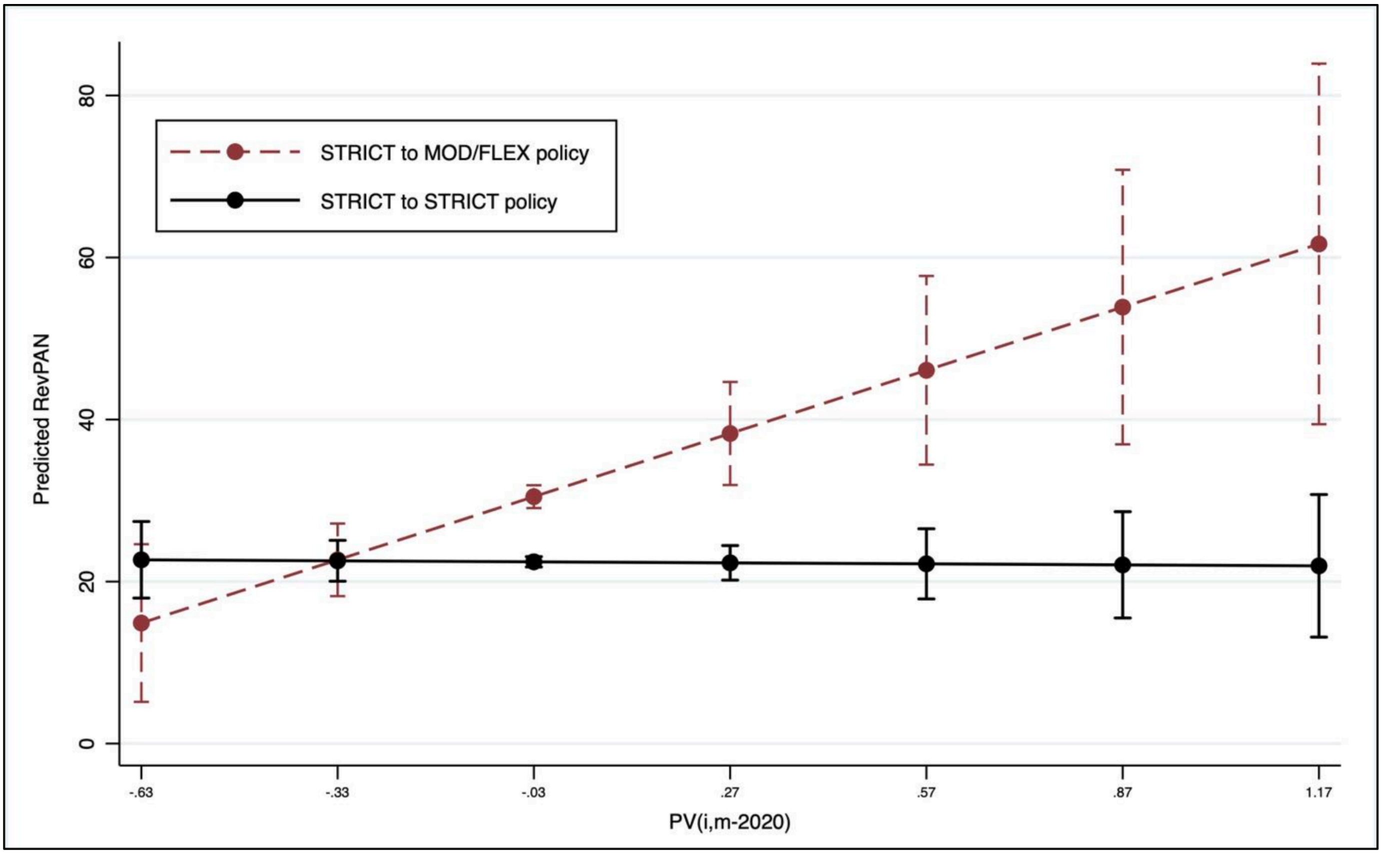

Fig. 3. Predicted RevPAN for different levels of $PV_{(i,m)}$ to compare moderate/flexible cancellation policies with the strict ones. Note: a) The plot is based on the estimated coefficients used in model M6 in Table 6. b) 90% CI is displayed. c) Price delta = $PV_{(i,m\text{-}2020)}$; and varies between the 10th and 90th percentiles of the distribution.

and flexible cancellation policies for PV^{2020}.[20]

Second, according to Bresciani et al. [12], as a result of the Covid-19 outbreak, a significant share of the Airbnb demand migrated from room-style accommodations (i.e., Private or Shared Rooms) to apartment-style ones (i.e., Entire Apartments) in order to avoid social contacts. It could therefore be reasonable to hypothesize that differences in OccR, RevPAN, and pricing could have arisen for rooms, compared to apartments, as they were differently exposed to Covid-19. For this reason, in order to validate the robustness of our results, we estimated the model of the sample of Entire Apartments only, thus excluding all room-style listings (see Tables A16 and A17 in the Online Appendix). We found similar results, and all the findings in Sections 5.2.1 and 5.2.2 were fully confirmed.

6. Discussion and conclusions

This paper provides an empirical contribution that was aimed at understanding how service providers in the Airbnb context (namely the hosts) have reacted to the *super economic shock* introduced by the Covid-19 pandemic [2]. We have studied the case of Rome, one the largest touristic markets in the world and the most important in Italy. Since the demand has been affected by a general 70% to 80% decline in reservations, and since the decreasing supply rate is five times lower than the demand one, we argue that to avoid being crushed to a great extent by the recession and by the increased competition between peers, Airbnb service providers had to employ appropriate marketing choices to address the emerging needs of its customers [12,16].

Thus, this paper has analysed the activism of Airbnb hosts by studying how they leveraged on price adjustments and flexible cancellation policies (i.e., the proposition of *Moderate/Flexible* services) to achieve higher economic returns, and also by comparing the pre and post Covid-19 pandemic periods. We noticed that the pandemic determined a significant increase in the marketing activism of Airbnb hosts (in other words, new customer preferences emerged in response to the Covid-19 outbreak). Indeed, the average variation in the prices increased significantly (in absolute values), and the change rate of cancellation policies, which has mainly polarized toward more flexible services, also increased significantly. We have also found that this emerging marketing activism is significantly correlated with economic returns, as: i) the proposition of *Moderate/Flexible* policies is positively correlated with both demand and economic returns, and ii) the proposition of *Moderate/Flexible* policies is a moderator of the classical relationship between prices and demand, or economic returns, for larger variations in prices.

We have interpreted these results in light of multiple research streams. First, following Porter & Rivkin [6], we have confirmed that a competitive repositioning is needed, and likely to occur, following a shock. This is particularly true for the touristic industry since, amongst others, the demand preferences have changed, and this has resulted in an emerging segmentation of customers [12,16]. Therefore, according to Armstrong & Rochet [37], we have interpreted the positive and significant joint effects of *Moderate/Flexible* policies and price adjustments as the emergence of screening mechanisms that are able to sort

[20] For the sake of clarity, both tables provide a statistical testing of whether there is a significant difference between the coefficient associated with each policy. The tests always confirmed that the coefficients were not significantly different, except for the linear coefficients of Moderate and Flexible policies when used to predict the Occupation Rate, where a significant difference could be observed at the 10% confidence level.

customers who have different elasticities in order to extract higher returns. Indeed, our results confirm that although the adoption of flexible policies was not able to create significant value in the 'stationary' pre-pandemic condition (i.e., in 2019), significant increases in the hetherogeneity of the preferences of customers are likely to have been generated by the Covid-19 outbreak, thus creating the premises for the exploitation of such emerging customer segments (e.g., high-end travelers or business ones with the need of flexibility, or people with uncertainty at the moment of reservation) through sorting and price discrimination.

6.1. Theoretical and practical implications

This research paves the way for multiple implications that could be of interest for both academics involved in the tourism and marketing management field and managers in the touristic sector, as relevant insights that have effects that go well beyond the Covid-19 pandemic have been derived from the analysis. At a glance, our analyses show how complex the mechanisms behind online marketplaces are, with the Covid-19 pandemic, in the case of Airbnb, further increasing the complexity of the choices that can be taken by service providers to exploit profitable returns.

From the theoretical point of view, we provide further layers to the literature stream that analyses the impact of shocks on the touristic industry [1]. Indeed, together with Bresciani et al. [12], who pointed out that having an entire isolated apartment has resulted in a distinct, differentiating feature on the post Covid-19 Airbnb market, we have shown that, apart from structural characteristics, which cannot be modified by definition, hosts can limit the negative impact of shocks through specific marketing choices aimed at screening and discriminating the emerging needs of their customers.

From a managerial perspective, since the Covid-19 pandemic has introduced uncertainty at the moment of the reservation, we have shown that being able to recognize how the exogenous shock has reconfigured the needs of customers and, consequently, how to discriminate them by providing specific services, can result in a positive differential of economic returns. Consistently, moderate and flexible policies are able to discriminate customers with different price elasticities, and hosts therefore have to be aware of the fact that when proposing flexible reservation terms, less price-sensitive customers are likely to be sorted. Following the qualitative findings of Farmaki et al. [13], who stated that hosts were willing to increase prices in the hope of covering the losses due to the Covid-19 pandemic, we provide a complementary finding, that is, we suggest that the proposition of *Moderate/Flexible* services can help hosts to pursue this marketing choice (in this case, taking charge of the risks associated with the possibility of facing last-minute cancellations).

6.2. Limitations and future research

This research is not exempt from limitations. On the one hand, two different types of concern, related to the geographical and time scope of the research, which, in our opinion, can be the starting point for future research on this topic, are likely. First, we conducted our analysis on the city of Rome, which is the largest touristic market in Italy (and the largest Italian Airbnb market), and one of the most popular tourist destinations in the world. Since Rome represents a certain typology of destination, as it is different, for instance, from rural destinations, it may be of interest for researchers who are interested in testing the replicability of our results in different contexts, such as rural destinations or major tourist spots with more marked seasonal patterns (e.g., seaside destinations). Second, despite having conducted our analysis on a recent and rich database, it may be of interest to consider the future evolution of the marketing choices presented in this paper to test our hypotheses for the year 2021 or 2022 since the tourism industry is (gradually) returning to normality. Consistently, further research could be directed toward analysing whether the choices highlighted in this study, and their effects, will persist in a post-pandemic period. We believe that if more granular data were available (e.g., changes in marketing choices observed once per month), further insights could be derived from this study. Indeed, although we analysed the efficacy of specific marketing choices in response to an exogenous shock, we were not able to measure whether, in the short and medium terms, first mover advantages could arise.

CRediT authorship contribution statement

Luigi Buzzacchi: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Funding acquisition. **Francesco Luigi Milone:** Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Funding acquisition. **Emilio Paolucci:** Conceptualization, Resources, Writing – review & editing, Supervision, Funding acquisition. **Elisabetta Raguseo:** Validation, Resources, Data curation, Writing – review & editing, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We acknowledge FULL (The Future Urban Legacy Lab), a multidisciplinary centre of Politecnico di Torino, for the provision of the Airbnb data.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.im.2023.103857.

References

[1] B.W. Ritchie, Y. Jiang, A review of research on tourism risk, crisis and disaster management: launching the annals of tourism research curated collection on tourism risk, crisis and disaster management, Ann. Tourism Res. 79 (2019), 102812, https://doi.org/10.1016/j.annals.2019.102812.
[2] S. Dolnicar, S. Zare, COVID19 and Airbnb-Disrupting the disruptor, Ann. Tourism Res. (2020) 1–4, https://doi.org/10.1016/j.annals.2020.102961.
[3] Y.C. Chang, C.H. Ku, D.D. Le Nguyen, Predicting aspect-based sentiment using deep learning and information visualization: the impact of COVID-19 on the airline industry, Inf. Manag. 59 (2) (2022), 103587, https://doi.org/10.1016/j.im.2021.103587.
[4] L. Li, Y. Tong, L. Wei, S. Yang, Digital technology-enabled dynamic capabilities and their impacts on firm performance: evidence from the COVID-19 pandemic, Inf. Manag. 59 (8) (2022), 103689, https://doi.org/10.1016/j.im.2022.103689.
[5] S. Li, Y. Wang, R. Filieri, Y. Zhu, Eliciting positive emotion through strategic responses to COVID-19 crisis: evidence from the tourism sector, Tourism Manag. 90 (2022), 104485, https://doi.org/10.1016/j.tourman.2021.104485.
[6] Porter, M.E., & Rivkin, J.W. (2000). *Industry transformation*. Harvard Business School Background Note 701-008, July 2000. Source: https://www.hbs.edu/faculty/Pages/item.aspx?num=27306.
[7] D. Sedera, C.W. Tan, D. Xu, Digital business transformation in innovation and entrepreneurship, Inf. Manag. (2022), 103620, https://doi.org/10.1016/j.im.2022.103620.
[8] B. Yao, R.T.R. Qiu, D.X.F. Fan, A. Liu, D. Buhalis, Standing out from the crowd–an exploration of signal attributes of Airbnb listings, Int. J. Contemp. Hospitality Manag. 31 (12) (2019) 4520–4542, https://doi.org/10.1108/IJCHM-02-2019-0106.
[9] K.S. Moorthy, Market segmentation, self-selection, and product line design, Mark. Sci. 3 (4) (1984) 288–307, https://doi.org/10.1287/mksc.3.4.288.
[10] P. Kotler, G. Armstrong, J. Saunders, V. Wong, Principles of Marketing, 3rd European ed., Harlow, England, 2002.
[11] D. Guttentag, Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector, Current Issues in Tourism 18 (12) (2015) 1192–1217, https://doi.org/10.1080/13683500.2013.827159.

[12] S. Bresciani, A. Ferraris, G. Santoro, K. Premazzi, R. Quaglia, D. Yahiaoui, G. Viglia, The seven lives of Airbnb. The role of accommodation types, Ann. Tourism Res. 88 (2021), 103170, https://doi.org/10.1016/j.annals.2021.103170.
[13] A. Farmaki, C. Miguel, M.H. Drotarova, A. Aleksić, A.Č. Časni, F. Efthymiadou, Impacts of Covid-19 on peer-to-peer accommodation platforms: host perceptions and responses, Int. J. Hosp. Manag. 91 (2020), 102663, https://doi.org/10.1016/j.ijhm.2020.102663.
[14] Gerwe, O. (2021). *The Covid-19 pandemic and the accommodation sharing sector: effects and prospects for recovery*. technological forecasting and social change, 167, Article 120733. 10.1016/j.techfore.2021.120733.
[15] Hu, M., & Lee, A.D. (2020). *Airbnb, COVID-19 risks and lockdowns: local and global evidence*. SSRN Working Paper. Available at SSRN: https://ssrn.com/abstract=3589141 or https://doi.org/10.2139/ssrn.3589141.
[16] J. De Vos, The effect of COVID-19 and subsequent social distancing on travel behavior, Transp. Res. Interdisciplinary Perspectives 5 (2020), 100121, https://doi.org/10.1016/j.trip.2020.100121.
[17] K. Xie, Z. Mao, J. Wu, Learning from peers: the effect of sales history disclosure on peer-to-peer short-term rental purchases, Int. J. Hosp. Manag. 76A (2019) 173–183, https://doi.org/10.1016/j.jhtm.2021.04.016.
[18] T.A. Ghebreyesus, Opening Remarks At the Media Briefing On COVID-19, March 11, WHO, 2020. Source, https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19-11-march-2020.
[19] E. Mele, R. Filieri, M. De Carlo, Picture of a crisis. Destination marketing organizations' Instragram communication before and during a global health crisis, J. Bus. Res. 163 (2023), 113931, https://doi.org/10.1016/j.jbusres.2023.113931.
[20] UNWTO, (2021a). *Tourism and COVID-19 – unprecedented economic impacts*. Source: https://www.unwto.org/tourism-and-covid-19-unprecedented-economic-impacts.
[21] T. Dogru, M. Mody, C. Suess, Adding evidence to the debate: quantifying Airbnb's disruptive impact on ten key hotel markets, Tourism Manag. 72 (2019) 27–38, https://doi.org/10.1016/j.tourman.2018.11.008.
[22] V. Zoğal, A. Domènech, G. Emekli, Stay at (Which) Home: second Homes during and after the COVID-19 Pandemic, J. Tourism Futures 8 (1) (2020) 125–133, https://doi.org/10.1108/JTF-06-2020-0090.
[23] M. Godovykh, R.M. Back, D. Bufquin, C. Baker, J. Park, Peer-to-peer accommodation amid COVID-19: the effects of Airbnb cleanliness information on guests' trust and behavioral intentions, Int. J. Contemp. Hospitality Manag. Forthcoming (2022), https://doi.org/10.1108/IJCHM-12-2021-1508.
[24] L. Shen, S. Wilkoff, Cleanliness is next to income: the impact of Covid-19 on short-term rentals, J. Reg. Sci. 62 (3) (2022) 799–829, https://doi.org/10.1111/jors.12581.
[25] N. Singh, Y. Teotia, T. Singh, P. Bhardwaj, COVID-19 pandemic: *a sentiment and emotional analysis of modified cancellation policy of Airbnb*, in: A. Abraham, O. Castillo, D. Virmani (Eds.), Proceedings of 3rd International Conference on Computing Informatics and Networks. Lecture Notes in Networks and Systems 167, Springer, Singapore, 2021.
[26] T. Dogru, M. Mody, C. Suess, N. Line, M. Bonn, Airbnb 2.0: is it a sharing economy platform or a lodging corporation? Tourism Manag. 78 (November) (2020), 104049 https://doi.org/10.1016/j.tourman.2019.104049.
[27] Buzzacchi, L., Grilli, L., & Milone, F.L. (2022). *Seizing local entrepreneurial opportunities in the platform-based era: airbnb, gig entrepreneurs and middlemen*. Working Paper.
[28] R. Sainaghi, G. Abrate, A. Mauri, Price and RevPAR determinants of Airbnb listings: convergent and divergent evidence, Int. J. Hosp. Manag. 92 (2021), 102709, https://doi.org/10.1016/j.ijhm.2020.102709.
[29] U. Gunter, I. Önder, B. Zekan, Modeling Airbnb demand to New York City while employing spatial panel data at the listing level, Tourism Manag. 77 (February 2019) (2020), https://doi.org/10.1016/j.tourman.2019.104000.
[30] U. Gunter, I. Önder, Determinants of Airbnb demand in Vienna and their implications for the traditional accommodation industry, Tourism Econ. 24 (3) (2018) 270–293, https://doi.org/10.1177/1354816617731196.
[31] B. Benítez-Aurioles, The role of distance in the peer-to-peer market for tourist accommodation, Tourism Econ. 24 (3) (2018) 237–250, https://doi.org/10.1177/1354816617726211.
[32] D. Boto-Garcia, Heterogeneous price adjustments among Airbnb hosts amid COVID-19: evidence from Barcelona, Int. J. Hosp. Manag. 102 (2022), 103169, https://doi.org/10.1016/j.ijhm.2022.103169.
[33] A. Hidalgo, M. Riccaboni, A. Rungi, F.J. Velazquez, COVID-19, social distancing and guests' preferences: impact on peer-to-peer accommodation pricing, Current Issues in Tourism (2021) 2571–2577, https://doi.org/10.1080/13683500.2021.1963215.
[34] S. Goyat, The basis of market segmentation: a critical review of literature, Eur. J. Bus. Manag. 3 (9) (2011) 45–54.
[35] B. Tong, U. Gunter, Hedonic pricing and the sharing economy: how profile characteristics affect Airbnb accommodation prices in Barcelona, Madrid, and Seville, Current Issues in Tourism (2020) 1–20, https://doi.org/10.1080/13683500.2020.1718619.
[36] R.D. Wang, M.J. Shaver, Competition-driven repositioning, Strategic Manag. J. 35 (11) (2014) 1585–1604, https://doi.org/10.1002/smj.2167.
[37] M. Armstrong, J.C. Rochet, Multi-dimensional screening: a user's guide, Eur. Econ. Rev. 43 (4–6) (1999) 959–979, https://doi.org/10.1016/S0014-2921(98)00108-1.
[38] L. Buzzacchi, F. Governa, C. Iacovone, F.L. Milone, Italy is in the Air(bnb): the uneven diffusion of short-term rental markets between urban locations and selective tourism destinations, Scienze Regionali, Italian J. Regional Sci. (2022) 229–252, https://doi.org/10.14650/103302, 2/2022.
[39] K. Xie, Z. Mao, The impacts of quality and quantity attributes of Airbnb hosts on listing performance, Int. J. Contemp. Hospitality Manag. 29 (9) (2017) 2240–2260, https://doi.org/10.1108/IJCHM-07-2016-0345.
[40] C. Farronato, A. Fradkin, The welfare effects of peer entry: the case of airbnb and the accommodation industry, Am. Econ. Rev. 112 (6) (2022) 1782–1817, https://doi.org/10.1257/aer.20180260.
[41] R. Deboosere, D.J. Kerrigan, D. Wachsmuth, A. El-Geneidy, Location, location and professionalization: a multilevel hedonic analysis of airbnb listing prices and revenue, Regional Stud. Regional Sci. 6 (1) (2019) 143–156, https://doi.org/10.1080/21681376.2019.1592699.
[42] E. Ert, A. Fleischer, N. Magen, Trust and reputation in the sharing economy: the role of personal photos in Airbnb, Tourism Manag. 55 (2016) 62–73, https://doi.org/10.1016/j.tourman.2016.01.013.
[43] U. Gunter, What makes an Airbnb host a superhost? Empirical evidence from San Francisco and the Bay Area, Tourism Manag. 66 (2018) 26–37, https://doi.org/10.1016/j.tourman.2017.11.003.
[44] R. Mayya, S. Ye, S. Viswanathan, R. Agarwal, Who forgoes screening in online markets and why? Evidence from Airbnb, MIS Q. 45 (4) (2020) 1745–1776, https://doi.org/10.25300/MISQ/2021/15335.
[45] D. Boto-García, M. Mayor, P De la Vega, *Spatial Price mimicking on Airbnb: multi-host* vs *single-host*, Tourism Manag. 87 (2021), 104365, https://doi.org/10.1016/j.tourman.2021.104365.
[46] F. Kleibergen, R. Paap, Generalized reduced rank tests using the singular value decomposition, J. Econom. 133 (2006) 97–126, https://doi.org/10.1016/j.jeconom.2005.02.011.
[47] G.A. Akerlof, The market for "lemons": quality uncertainty and the market mechanism, Q. J. Econ. 84 (3) (1970) 488–500, https://doi.org/10.2307/1879431.
[48] J.A. Mirrlees, The optimal structure of incentives and authority within an organization, The Bell J. Econ. 7 (1) (1976) 105–131, https://doi.org/10.2307/3003192.
[49] J.E. Stiglitz, Monopoly, non-linear pricing and imperfect information: the insurance market, Rev. Econ. Stud. 44 (3) (1977) 407–430, https://doi.org/10.2307/2296899.

Luigi Buzzacchi is Full Professor at Politecnico di Torino (Italy), where he teaches courses in Urban Economics and Industrial Organization. His-research interests lie in the area of urban and regional economics, insurance and financial markets, firm size, and spatial competition. He is author of several publications on international peer-reviewed journals such as Research Policy, Journal of Banking and Finance, Journal of Corporate Finance or International Journal of Industrial Organization.

Francesco Luigi Milone is a Post-Doc at Politecnico di Torino (Italy) and he is teaching assistant in Company Economics and Innovation Management. Francesco's research interests focus on the industrial organization of short-term rental markets, tourism, and the economics of sports. He is author of publications on international and national peer-reviewed journals such as Tourism Management, European Urban and Regional Studies, Journal of Sports Economics or Italian Journal of Regional Science.

Emilio Paolucci is Full Professor at Politecnico di Torino, where he teaches Entrepreneurship and Business Planning, Strategy and Organization Theory and Company Economics. Furthermore, he has been Vice Rector for Technology Transfer. He is author of more than 100 publications on international and national journals including Information & Management, Current Issue in Tourism, Industrial and Corporate Change, New Technology, Work and Employment, e International Journal of Information Management.

Elisabetta Raguseo (PhD) is Associate professor of Strategy and Economics at Politecnico di Torino (Italy). She is Associate Editor of Information and Management and of Journal of Travel Research. She is in charge of the education pillar of the EIT Manufacturing at her university. She was part of the Group of Experts for the Observatory on the Online Platform Economy of the European Commission (mandate 2018–2021) and a Marie Curie research fellow at the business school Grenoble Ecole de Management (France) in the years 2014–2016. Her research and teaching expertise is in strategic management and digital transformation. Her research has been published in highly ranked, international journals including Information and Management, International Journal of Electronic Commerce, International Journal of Information Management and many more.