High tide, low price? Flooding alerts and hotel prices in Venice

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Abstract

This research explores the effects of High Tide alerts on hotel prices in Venice, a city that is vulnerable to the impacts of extreme climate events due to its fragile ecosystem and a long history of floods in the city center. By analyzing and combining price data from Booking.com with publicly available information on tides and weather, this study uses regression discontinuity design to test for changes in hotel prices when tide levels reach a critical threshold. The results offer insights into the sensitivity of hotel prices to weather alerts and provide valuable information on the potential impact of climate change on Venice's tourism-driven economy, with implications for the cost-benefit analysis of activating protective barriers for lagoon protection.

Keywords: Venice; high water; climate events; weather alerts; dynamic pricing; revenue management

1 Introduction

Climate change and weather uncertainty pose significant threats to tourism destinations. Sea level rise stemming from increasing average temperatures, and the higher frequency of extreme events negatively affect tourism establishments directly, damaging structures and infrastructures, and indirectly, curbing tourism demand. In this respect, Venice is one of the most emblematic cases, as its fragile ecosystem is the backbone of a superstar tourism destination. Over the centuries, the city has been prone to progressive submersion due to the joint effect of sea level rise, land subsidence, and episodes of High Tides (in Italian, *Acqua Alta*, which literally means high water) flooding the city center (Tosi et al.

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2013). The frequency and intensity of these episodes have increased over the last decades, arguably because of climate change (Umgiesser et al. 2021, Lionello et al. 2021).

Despite High Tides representing a peculiarity of the city, which (to some extent) could be perceived as a romantic trait by visitors, flooding is a source of discomfort, especially for inhabitants, and imposes non-negligible costs for the overall city's economy. As a result, in 2003 the Italian government decided to start the construction of a protection system, the so-called MOSE (from Experimental Electromechanical Module). MOSE consists of a set of mobile barriers located at the three lagoon inlets (Lido, Malamocco, and Chioggia) and managed by the *control room* where tide forecasts, system activation, and barriers maneuvers are handled. The barriers are activated when the forecast tide exceeds 110cm and allow to temporally isolate the lagoon from the Adriatic sea.

In non-risky periods, the barriers lay on the seabed while being filled with water. Once the sea level reaches the trigger point, the barriers are lifted by injecting compressed air into them. Typically, the lagoon remains closed for approximately five hours, taking into consideration the time required for the entire lifting process. However, the duration of closures can vary based on the severity of the event (Vergano et al. 2010). A significant time lapse of approximately 20 years passed before the MOSE construction project was completed after the initiation of its first phase, with the first activation having taken place on the 3rd of October 2020.

A lot of criticism was raised about MOSE project, especially concerning its environmental impacts and the huge construction and maintenance costs. Predictably, the case of Venice's fragility fuelled academic interest, with a few empirical studies attempting to quantify the costs and benefits of protecting the city from flooding (Caporin & Fontini 2016, Rosato et al. 2017, D'Alpaos & D'Alpaos 2021, Fontini et al. 2010), also considering alternative solutions to MOSE, and taking into account the unremitting climate change (Ammerman & McClennen 2000, Pirazzoli & Umgiesser 2006, Umgiesser 2020, Castelletto et al. 2008, Teatini et al. 2010, Comerlati et al. 2004). As per the literature evaluating the *Acqua Alta*'s damages, several costs must be considered, including direct costs to protect and restore buildings (most of them historical buildings), increased costs for the Venetian population (e.g., babysitting and elderly care costs), costs for reduced port and tourism activities (see Fontini et al. (2010) and Vergano et al. (2010) for more details on the methodology implemented and the overall estimates).

To the best of the authors' knowledge, the evaluation of damages to tourism activities has only considered the potential number of *discouraged tourists* when experiencing high water events, typically calculated by regressing severe High Tides events (tides above certain thresholds) on the number of monthly visitors, controlling for year and monthly fixed effects (Fontini et al. 2010). Estimates on the loss of tourism revenues are then computed by multiplying the number of missed visitors by the average daily expenditure.

Against this framework, our paper provides further evidence on the impact of High Tide events on the local tourism sector, by exploring another facet of the phenomenon, the indirect impact on revenues through price changes. More specifically, we analyze the effect of high water alerts, which are produced within 48 hours of anticipation of the forecast High Tide, on hotel price dynamics. For this purpose, we work with room daily prices listed by hotels on Booking.com, the leading OTA platform, during the months of November and December 2019, a period when Venice experienced severe *Acqua Alta* episodes. We match each record with publicly available data on tide forecast (from the

Centro Previsioni e Segnalazione Maree – Centre for the forecast and monitoring of tides), thus investigating the role played by high-water alerts in a quasi-experimental setting. Adopting regression discontinuity design, we test the existence of a significant change (jump) in hotel prices when water levels reach the 110cm threshold, which denotes a high-water episode for which alerts are produced and sent out, and also corresponds (since October 2020) to the cutoff point for the activation of the MOSE protective barriers.

The current work contributes to the literature on the impact of weather on tourism, within the broad framework of the current climate crisis. Specifically, it provides insights into the sensitivity of hotel prices to weather alerts, which are an example of public information, in line with the literature on dynamic pricing, especially Figini et al. (2022). Other factors, like structural hotel and room features, market competition, and air and water quality, that could also impact room fares, are controlled for. The study has relevant managerial and policy implications, given the climate change-led increasing frequency and intensity of these extreme events. Moreover, since the analysis is carried out in a pre-MOSE situation, our results shed light on another benefit (in terms of avoided price variations) associated with the activation of the protective barriers, thus providing policymakers with a more comprehensive cost-benefit analysis of lagoon protection.

High Tides in Venice represents indeed a unique phenomenon, given the city's fragile ecological balance, its rich history and art, and its status as a major tourism destination. However, the implications of our research extend far beyond this singular case. The analytical framework developed here has broad applicability to other scenarios in which climatic events, such as storms or tornadoes, are predicted to have economic implications for local agents. This framework offers a potentially valuable tool for assessing the economic consequences of climate-related alerts and could be applied in a variety of contexts beyond the scope of our current analysis. Furthermore, by focusing specifically on weather signaling rather than the event *per se*, our study enables us to explore agents' responsiveness to public information and assess the credibility of signals. By analyzing how individuals and organizations respond to external stimuli, our approach offers valuable insights into the dynamics of decision-making in an increasingly volatile environment.

2 Literature Review

We mainly contribute to the growing literature on the impact of climate, and more specifically weather conditions, on the economy (see Dell et al. 2014 for a comprehensive survey). The weather impacts the economy in several ways, for example triggering exogenous shocks in markets, thus leading to supply-side shortages of goods, with consequent inflationary effects (Heinen et al. 2018) that modify demand indirectly (as is the case for energy, see Mu 2007). The psychological dimension of individual choices is also affected in diverse domains such as college enrollment (Simonsohn 2010) or financial investment (Hirshleifer & Shumway 2003). In some specific markets, it can also directly modify the quality of the good; think about wine production (Ashenfelter 2008) or tourism (Shih et al. 2009, Ridderstaat et al. 2014).

In the tourism market, the weather is unsurprisingly considered a key factor affecting both sides of the market, as it shapes: (i) tourists' travel decisions, activities carried out while at the destination, and the ex-post evaluation of tourists' experiences; (ii) the supply-side pricing strategy, especially when demand is strongly affected by seasonality. As regards the first point, it might be trivial to recall that some categories of tourists are particularly weather-sensitive, especially when leisure activities are considered (Becken 2012). Beach tourists positively react to warmer and sunnier weather (Muñoz et al. 2023), while snow depth is the most important factor affecting winter mountain tourists (Steiger 2011). Weather does not only affect the decision of travelling to a specific destination but also the length of stay, which might increase (decrease) if the meteorological conditions are better (worse) than expected (Becken & Wilson 2013). The spending pattern of tourists (Baños Pino et al. 2022) and the intra-destination mobility (McKercher et al. 2015) are also affected.

The relevance of the weather for tourism increases with the climate crisis, as climate change is linked to the increase in the number and intensity of extreme events (draughts, hurricanes, etc). Climate change can have both positive and negative effects, depending on the event, the destination, and the type of tourism. More specifically, the literature has been mainly looking at the mountain and seaside tourism (for in-depth reviews, respectively see Steiger et al. 2019 and Arabadzhyan, Figini, García, González, Lam-González & León 2021). In such a framework, researchers generally look at the physical (variation in the number of arrivals or overnights, see Rosselló et al. 2020) and behavioral (variation in the type of activities carried out while at destination, see Hübner & Gössling 2012 and Arabadzhyan, Figini & Vici 2021) impact of weather and climate events, but just a few papers analyze the impact on prices. Bernstein et al. (2019) investigate the negative impact of sea level rise on prices in the real estate market, while Lodi et al. (2023) study the public finance response to flooding events, with implications for the public budget.

As regards the ex-post evaluation, there is scarce but interesting literature showing how, from a psychological perspective, the weather affects mood, thinking, and judgments (Klimstra et al. 2011). As regards tourism services, Brandes & Dover (2022) recently show that unpleasant weather negatively affects the evaluation of accommodation services. Controlling for the weather in their origin country, they find that rain is associated with a higher probability of writing reviews and with lower rating scores. This is likely the effect of the lower opportunity cost of time when raining and the bad mood associated with bad weather. More in general, research has shown that the weather significantly impacts tourists' overall satisfaction with their travel experience. For example, tourists who experience favorable weather during their trip tend to rate their overall experience higher compared to tourists who experience unfavorable weather (Jeuring 2017, Jeuring & Peters 2013). A summary of the literature related to the impact of weather and climate on tourists' decisions, activities, and ex-post evaluation is in Table 1, Panel A.

Our work adds to the existing body of literature on how tourism firms, specifically hotels, respond to external shocks. In this regard, previous studies have examined the strategies implemented by tourism firms to manage different crises, particularly with respect to revenue management practices (Viglia et al. 2021). In the case of weather events, Zirulia (2016) finds an impact on the pricing strategies of tourism firms, especially when there is a discrepancy between expected and actual weather conditions. Figini et al. (2022) developed a model where good weather signals (i.e., weather forecasts) positively affect accommodation prices, with greater effects observed when the signals are more accurate and the ex-ante uncertainty of the weather is high, such as during the low season.

During and in the aftermath of natural disasters, service providers may implement specific policies aimed at reducing revenue losses caused by a decrease in arrivals (Okuyama 2018, Pérez-Granja et al. 2022). On the other hand, when it comes to sanitary crises, Zaki (2022) studies how flexible revenue management, especially dynamic pricing, has helped hotels react to the COVID-19 pandemic. Additionally, Hao et al. (2020), Garrido-Moreno et al. (2021), and Japutra & Situmorang (2021) all include revenue management strategies as part of their agenda to help businesses adapt and recover in times of pandemic. Meanwhile, Denizci Guillet & Chu (2021) and Giousmpasoglou et al. (2021) explore how revenue management is implemented during crises or low-demand periods by interviewing hotel Revenue Management executives.

Economic downturns also require a careful design of strategies. Interestingly, Kim et al. (2019) and Enz et al. (2009) suggest that, within the different crisis-coping strategies, abrupt price discounts might be counterproductive and hence represent a sub-optimal strategy. As discussed in Gehrels & Blanar (2013), rate dilutions and price wars might jeopardize future recovery, having positive effects only in the very short term. Finally, from a broader perspective, macroeconomic shocks might affect pricing strategies, also according to their business structure. In this regard, Blengini & Heo (2020) find that while chain hotels are more responsive to macro shocks, franchised hotel prices are mostly driven by local market disturbance, and independent hotels tend to adjust their prices in response to supply shocks. A summary of the literature related to how the supply side copes with the impact of climate and other external shocks is in Table 1, Panel B, at the end of which our paper's contribution is also reported for comparison purposes.

Reference	**Research focus**	**Context, methodology, and sample**	**Findings**
Panel A - The impact of weather and climate on tourists' decisions and ex-post evaluation of the experience			
Arabadzhyan, Figini & Vici (2021)	The impact of climate conditions on the destination image	Data mining of images posted on social media for a set of European islands	Climate conditions and events affect sentiment and activities carried out, with implications on the destination image
Baños Pino et al. (2022)	The impact of weather on tourism expenditure	Cruise passengers' onshore expenditure during different stopovers at Gijón (Spain)	Adverse weather conditions reduce onshore expenditure, with significant impact on the local economy
Becken (2012)	The impact of weather on tourism trips and activities	Time-series analysis (2000-2010) of New Zealand west-coast	Weather conditions do not affect the number of visits, but do affect the activities carried out at destination
Becken & Wilson (2013)	The impact of weather on tourism activities	Survey of 436 International tourists visiting New Zealand in 2009-10	Weather drives important changes in tourism activities, especially in early season, with links to satisfaction

Bernstein et al. (2019)	The impact of sea level rise on real estate prices	460,000 sales of residential properties between 2007 and 2016 in the US	Coastal properties exposed to projected sea level rise sell at a 7% discount relative to similar properties; this is not matched by an equivalent change in rental prices
Brandes & Dover (2022)	The impact of weather conditions on online reviews	Analysis of 300,000 text reviews and rating scores	More reviews are written on rainy days, with weather at home negatively affecting rating scores
Hübner & Gössling (2012)	The impact of extreme weather on pre-determined understandings	Survey and semi-structured interviews in Martinique	Extreme weather negatively affects satisfaction, especially for first-time visitors
Jeuring (2017)	Weather perception in Northern countries	Survey among domestic camping tourists in the Netherlands	The weather salience is a relevant factor driving tourism decisions
Jeuring & Peters (2013)	The narrative of weather in the travel blogs	Qualitative analysis of 200 randomly selected posts on a Dutch travel blog	Identification of several ways in which weather affects experience and satisfaction
Klimstra et al. (2011)	The impact of weather on personal mood	Match between self-reported mood and weather indicators for 497 adolescents	Four different types of reaction are identified, with reactivity depending on family links
McKercher et al. (2015)	The impact of weather on tourists' behavior	Survey and GPS tracking of tourists in Hong Kong	Weather has a limited impact on urban tourists, affecting satisfaction for only a limited fraction of visitors
Muñoz et al. (2023)	The impact of climatic variables on tourism demand	Interregional tourism flows by Spanish resident, 2011-15	The sensitivity of domestic tourism demand also depends on the different climatic conditions between home and destination
Pérez-Granja et al. (2022)	The impact of natural disasters on tourism expenditure	Difference-in-Difference analysis applied to a volcanic eruption in Gran Canaria	Expenditure increased in the eruption and post-eruption phases, explained by prosocial behavior of tourists
Rosselló et al. (2020)	The impact of extreme events on tourism demand	International panel analysis of different types of natural and human-made disasters	Tsunamis, floods, and eruptions are the most significant factors adversely affecting international tourism

Steiger (2011)	The sensitivity of ski tourism to climate change	Winter of 2006-07 in Austria used as an analogue year to represent future scenarios	Warm temperature and less snow-depth redistribute skiers between resorts more than reducing the numbers
Panel B - Dynamic pricing strategies and supply-side response to cope with external shocks			
Blengini & Heo (2020)	Analysis of pricing strategies used to respond to macroeconomic factors	Econometric analysis of the performance of Swiss hotels in the 2000-18 period	Pricing strategies implemented to respond to external factors depend on the hotel's business model and proprietary structure
Denizci Guillet & Chu (2021)	Crisis management in the Covid-19 case	Semi-structured interviews with 26 revenue executives, mainly based in Asia	The priority of the different revenue management processes changed during the pandemic
Enz et al. (2009)	Analysis of pricing, revenue, and performance dynamics	Empirical analysis of 67,008 hotels over the 2001-07 period	Revenue performance changes with occupancy rates, suggesting that lodging demand is inelastic in local markets
Figini et al. (2022)	The impact of weather forecasts on prices	Theoretical (Bayesian rational choice) and empirical (hedonic model) analysis applied to the case of Rimini	Forecasts of bad weather decrease posted prices, the intensity increasing with the accuracy of the signal and the ex-ante uncertainty of the weather
Garrido-Moreno et al. (2021)	Crisis management in the Covid-19 case	A quantitative survey of 237 Spanish hotel managers	More flexibility, especially in applying the cancellation policy, was used
Gehrels & Blanar (2013)	Analysis of pricing, revenue, and performance dynamics	Qualitative analysis of two hotels in Prague during and after the 2008 financial crisis	Rate dilution, discounts, and price wars should be resisted in times of crises, to better prepare the recovery
Hao et al. (2020)	Crisis management in the Covid-19 case	Development of a Covid-19 management framework, applied to the Chinese scenario	Revenue management is perceived as a useful tool for post-disaster recovery
Kim et al. (2019)	Tourism demand recovery after a crisis	Property-level performance analysis of the hospitality sector in Houston (US)	Discounts alleviate occupancy loss, not RevPAR loss, delaying both occupancy and RevPAR recovery times

Okuyama (2018)	Tourism demand recovery after a crisis	Contingent behavior method applied to a hypothetical scenario	Discounting policies can be applied, but only in the last step of the recovery process
Viglia et al. (2021)	Crisis management in the Covid-19 case	Mixed method (interviews and experiment)	During a crisis, hoteliers are more willing to share their data in a reciprocal context and to introduce revenue management techniques
Zaki (2022)	Crisis management in the Covid-19 case	Value stream mapping and wavelet analysis applied in Egypt	The use of revenue management is associated with hotel's efficiency in the short and medium term
Zirulia (2016)	The impact of weather forecasts on welfare	Theoretical model (Bayesian rational choice)	Once prices are set, the accuracy of forecasts increase (decrease) consumer surplus (profits)
Our contribution			
This paper	The impact of publicly available weather signals on hotels' prices	Regression Discontinuity Design applied to prices posted on Booking.com, in Venice	The weather alert of a High Tide episode has a significant negative impact on prices

Table 1: Overview of papers on the impact of weather and climate on tourists' decisions and ex-post evaluation of the experience (panel A) and on Dynamic pricing strategies and supply-side response to cope with external shocks (panel B)

In terms of methodology, we contribute to the popularity of regression discontinuity design (RDD) in tourism studies. RDD is a statistical approach that involves comparing outcomes between groups of subjects who are just above or below a certain threshold. A key advantage of RDD is that it can control for confounding variables that might otherwise bias the results, making RDD particularly useful for studying interventions that are implemented abruptly. In the field of tourism research, RDD has been used very rarely, mainly to study policy interventions (in terms of changes in regional policy, O'Brochta 2017; Deng et al. 2019; market regulation in the Airbnb market, Koster et al. 2021; financial incentives to the tourism sector, Silva et al. 2023) or the impact of retirement on tourism consumption (Deng et al. 2022).

3 Data

3.1 Case study

Venice is an iconic cultural tourism destination, with more than 13 million yearly stays (Comune di Venezia 2020). Tourists are mostly international (85% of overnight stays are from foreigners) while domestic visitors are often same-day trippers, typically visiting Venice over the weekend. According to local statistics, most tourists stay in the Historic City center, with more than 60% choosing traditional hotel services. The average length of stay is 2.3 days, with foreign tourists displaying slightly longer stays (Statistical Office of Veneto Region 2020). Besides its uniqueness in terms of architecture and cultural offer, which gained the city the UNESCO world-heritage status (UNESCO 1987), Venice is also known for its twofold fragility: social and environmental. From a social perspective, Venice is affected by a progressive depopulation, also driven by increasing housing prices. The substitution of permanent residents with temporary residents (tourists and second-home owners) is one of the characteristics of the so-called tourism gentrification process, which is strongly affecting many cities, including Venice (Salerno & Russo 2022). From an environmental perspective, Venice displays some very peculiar characteristics, being a low-lying lagoon city. The most known environmental challenge is the one imposed by High Tide phenomena (in Italian, *Acqua Alta*) causing temporal disruption to residents' life, and tourism activities. In the long run, *Acqua Alta* is also linked to further damages, such as erosion, sedimentation, and subsidence. In November 2019, the city experienced the most severe *Acqua Alta* episode since the late 1960s, with dramatic effects on the local economy.

3.2 Data description

Our analysis uses three types of daily information: (i) Room prices, collected with room and hotel characteristics; (ii) Tide information; and (iii) Weather conditions, including air and water quality indicators. In the following paragraphs, we provide a detailed description of such data, including variable definitions.

3.2.1 Hotel data

Data on hotel prices have been retrieved from the Booking.com website through an ad-hoc built web crawler, covering the months of November and December 2019.[1] We only considered properties located in the Historic city center (and not in Mestre, the mainland part of Venice), being those potentially directly affected by High Tide phenomena. Figure 1 shows the geographic distribution of accommodation facilities.

The dataset contains 20,181 observations. Each record consists of a daily price for a two-guest room, with a private bathroom and breakfast included.[2] For each room and specific check-in date, we considered the price posted two days prior to the arrival, which coincides with the potential High Tide forecast (available 48 hours in advance). In total, we considered rooms belonging to 199 hotels. The price (expressed in the natural logarithm) acts as our dependent variable. Besides room-specific information related to price (e.g., if it has a view of the canal, the category, if it is located on the ground floor), the dataset contains information about the hotel's characteristics (number of stars, geographic location), time-varying hotel features (remaining capacity), cancellation policies

[1]This choice has been made to avoid unrealistic comparisons. As will be discussed later in the text, High Tide phenomena occur only in Autumn and Winter. Therefore, summer observations are not similar enough to winter observations to recreate the *ceteris paribus* condition (overlap assumption) that causal inference requires (Imbens & Lemieux 2008).

[2]This choice is in line with previous studies on hotel pricing (Guizzardi et al. 2022, Soler et al. 2019).

Figure 1: Geographic distribution of Venice accommodation facilities.

associated with the offer, and other features that could also impact the price, like local competition, and the day of the week. In Table 2 we present some descriptive statistics of the variables used in the paper.

Variable name	Description	Mean/%	SD	Min	Max
ln(`price`)	Room price (in logarithm)	4.97	0.59	3.43	7.51
`Puredouble`	=1 if room is double	0.52			
`Puretwin`	=1 if room is twin	0.03			
`Groundfloor`	=1 if room is on the ground floor	0.00			
`Nonrefundable`	=1 if booking has a non-refundable policy	0.94			
`Withview`	=1 if room has a view	0.23			
`Terrace`	=1 if room has a terrace	0.02			
`Only1room`	=1 if there is only one room left of this type	0.18			
`CatEconomy`	=1 if room category is economy	0.05			
`CatStandard`	=1 if room category is standard	0.41			
`CatSuperior`	=1 if room is superior	0.54			
`Weekend`	=1 if the date is weekend	0.22			
`November`	=1 if November	0.45			
`Competition`	Number of available rooms (of the same quality) in the same neighborhood	33.88	20.89	0	79
`Quality`	Categorical variable with the number of hotel stars	3.72	0.66	3	5

Table 2: Definition and descriptive statistics of the hotel variables ($N = 20,181$)

The average room price is 175€. Given the high heterogeneity in the sample, composed of 40% of three-star hotels, 48% of four stars hotels, and the remaining 12% of five-stars hotels, price displays a great dispersion (min=31; max=1819; s.d.=139.17). Only less than 1% of rooms are the most exposed to the flooding risk, being located on the ground floor. Rooms have been clustered into three main categories, where superior rooms represent 54% of the sample, followed by standard rooms (41%) and economy rooms (5%). 94% of offers have a non-refundable policy. As shown in Figure 1, hotels are concentrated around the most famous spots, with 33% located in San Marco *sestiere* (neighborhood), 19% in Castello, 19% in Cannaregio, 13% in Dorsoduro and Giudecca, 11% in Santa Croce and the remaining 5% located in San Polo.

3.2.2 Tide data

Given the main purpose of the study, we obtained detailed daily information on tides. Data are publicly available on the *Centro Previsioni e Segnalazioni Maree* website, which is the local authority for monitoring sea water height and, hence, for informing about forthcoming extreme high-tide events. For each day of the period under investigation, we collected information on the maximum tide in cms, `tide` (mean=96.69; st.dev.=26.10; min=53; max=181). In our empirical setting, we also take into account if the tide is increasing, compared to the previous day (`tideincreasing`; mean=0.47). Weather alerts are sent out when *Acqua Alta* events occur, being defined as situations when the water level is forecast to exceed 110cm above the ZMPS reference point (mareographic zero located in *Punta della salute*). This threshold, which is the one considered in other studies (e.g., Ferrarin et al. 2022, Umgiesser et al. 2021), triggers the MOSE activation (www.mosevenezia.eu).[3] Figure 2 shows the time-series of high-water episodes during

[3] *Acqua Alta* already occurs at 90cm, however with no relevant implications for residents and tourist activities (only 2% of city is flooded). When the tide reaches 110cm, 12% of the city is flooded, while

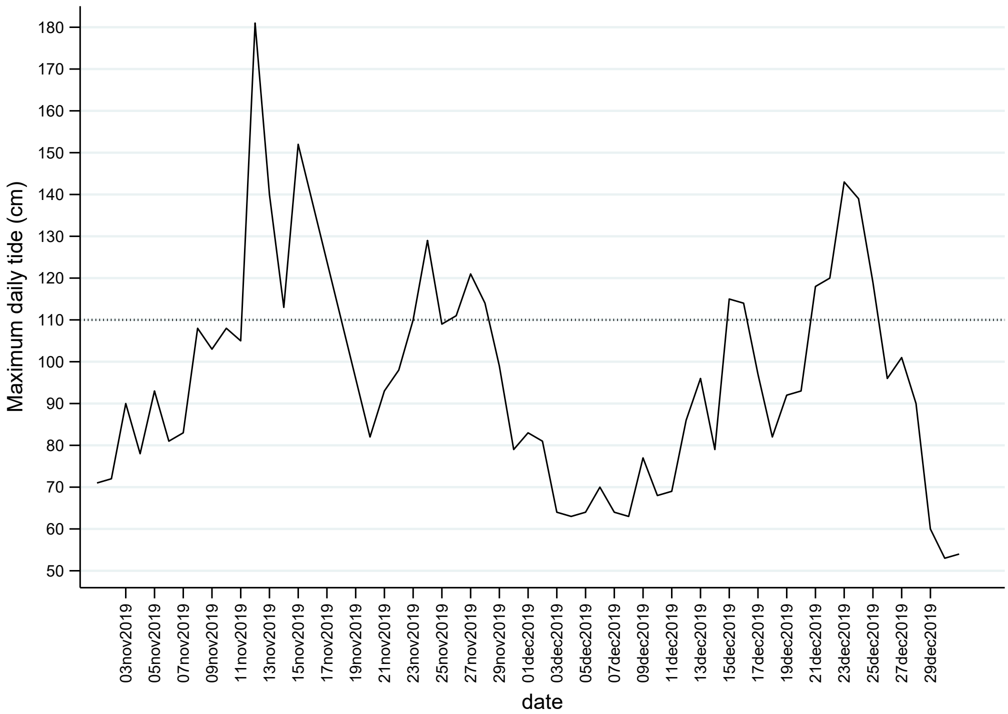

Figure 2: Temporal distribution of High Tide episodes during the study period.

the period under investigation. On the vertical axis, we display the maximum daily tide (in cm), with the horizontal line showing the days considered in our study. Overall, we detect 17 days over the threshold, clustered in 4 *Acqua Alta* episodes.

3.2.3 Weather, air, and water quality data

Daily data on weather, air, and water quality have been obtained from Arpa Veneto, the local agency for Environmental protection and monitoring. More specifically, we collected the following three subgroups of variables:

1. Water quality-related variables: temperature, salinity, chlorophyll, and turbidity;
2. Air quality-related variables: levels of PM10, PM2.5, NO2, and O3;
3. Weather-related variables: rain, pressure, air temperature, air humidity, solar radiation, and wind speed.

These variables are used as controls since, consistently with previous literature, they are likely to affect room prices. However, for sake of brevity, we omit an extended discussion of such variables as they are not the focus of our investigation. For more details, we refer the reader to Table 3, where the description of the variables used in the analysis, jointly with some descriptive statistics, is reported.

exceptional *Acqua Alta* occurs at 140cm (59% of the city is flooded). The maximum tides have been recorded in November 2019 (190cm) and November 1966 (195cm) with around 90% of the city flooded (CPSM 2022).

We built an integrated dataset with the above-mentioned variables, that allows for microeconometric analysis. In the dataset, each record represents a specific offer for a specific date (room price with related room and hotel characteristics), and the corresponding daily environmental and tide information.[4]

Variable name	Description	Unit of measure	Mean	SD	Min	Max
Lagoon Water quality						
`maxTemperature`	Maximum temperature	C°	10.77	2.32	6.02	14.54
`maxSalinity`	Maximum salinity	psu	26.71	2.31	22.23	30.56
`maxChlorophyll`	Maximum Chlorophyll level	µg/L	4.68	2.44	1.65	13.41
`maxTurbidity`	Max turbidity	ftu	47.86	33.37	12.61	234.55
Air quality						
`PM10`	Maximum PM10 concentration	µg/m3	25.35	16.04	5	72
`PM2.5`	Maximum PM2.5 concentration	µg/m3	20.92	13.39	7	65
`maxNO2`	Maximum NO2 concentration	µg/m3 293K	93.19	29.06	38	175
`maxO3`	Maximum O3 concentration	µg/m3 293K	39.91	18.59	2	69
Weather						
`maxRain`	Maximum rain	mm	1.14	2.38	0.00	11.60
`maxHpa`	Maximum pressure	hpa	1014.77	9.60	992.30	1036.70
`maxTempC`	Maximum temperature	C°	13.36	2.83	6.70	19.90
`maxHumidity`	Maximum humidity	%	94.65	7.13	69.00	100.00
`maxSolarradiation`	Maximum solar radiation	mj/m2	315.68	152.60	36.00	687.00
`maxWindspeed`	Maximum wind speed	m/s	7.02	3.63	2.50	24.10

Table 3: Definition and descriptive statistics for weather, air, and (lagoon) water characteristics ($N = 61$).

4 Methodology

4.1 Economic rationale

High Tides in Venice arguably impact agents behavior within the city, both on the demand and on the supply side. Theoretically, the High Tide can trigger opposite reactions: on the one hand, it is a distinctive and rather unique situation the visitor can live, thereby enhancing consumption and increasing the attractiveness of the city, with possible positive repercussions on local sellers too. However, this is more likely to happen if the High Tide is not “too high”. On the other hand, the High Tide can trigger prudential behaviors associated with risk (in terms of ruined vacation) or, more in general, with the perceived limitation of what can be seen and done in the city. This latter effect strongly grows in case of an exceptional High Tide, where also risks related to people safety start to emerge.

Before the first activation of the MOSE barriers to prevent *Acqua Alta* in 2020, the municipality of Venice had different systems to inform the citizens and the tourists about the potential rise of the water, and its consequent impact and related risk. Among these systems, there is an acoustic warning issued throughout the whole city of Venice in case the forecast of the tide in the following 3 days is above 110cm, the platforms allowing

[4] Some of the water quality-related variables in Table 3 were not available for all days. Supplementary materials contain the methodology used to extract information for missing days.

people to safely walk in the flooded parts of the city are positioned, and a series of visual announcements are shown all around the city, on screens and boards. For people who are not located in Venice, the warning can be sent by text message or email, through an automated system available to those who previously registered for this free service.[5] Regardless of the type of announcement, these systems signal an upcoming High Tide, clearly shared by citizens and tourists in the city.

As the warning signal is sent out only when the forecast tide is higher than 110cm, the alarm discriminates available information depending on the tide level itself. In fact, information used to forecast the tide level is already potentially available to both the supply and the demand side before the tide is expected to reach 110cm, but obtaining and processing this information can be costly. In this sense, such information is public but costly to use. When the warning is issued, this public information becomes easily and freely available to the agents, who can modify their decisions and behaviors. However, as the direction of this potential change is not straightforward to predict, we need empirical tools to investigate it. In this context, the regression discontinuity design (RDD) can be helpful.

This is confirmed by visual evidence of the alarm's effect on the price logarithm, as represented in the two binned scatterplots reported in Figure 3.[6] The left-hand panel reports the linear fit on the left and on the right of the threshold (at 110cm), while the right-hand panel reports the quadratic fit. The overall correlation between the variables is not evident a priori but, clearly, a discontinuity at the 110cm cutoff exists in both the linear and the quadratic fits. This suggests that the alarm may actually have a role in price-setting strategies. In particular, in both visual representations, the price logarithm drops from around 5.1 to around 4.9, that is, about 30 euro.

4.2 RDD Model & identification strategy

RDD is a quasi-experimental strategy that allows studying what is the effect of a treatment that is triggered when a certain variable – the *running variable* – is observed to be beyond a defined threshold. We can identify two different cases: (i) if the probability of being treated is 1 when the running variable is above the threshold (while it is 0 if it is below), we have a sharp regression discontinuity; (ii) if the probability is discontinuous at the threshold, smoothly passing from 0 to 1 without a clear jump, we have a fuzzy regression discontinuity. This latter case is observed when the treatment is not assigned to all the cases presenting a running variable above the threshold.[7]

Our case is a sharp RD because the warning hits the whole city and there is no way to manipulate the eligibility of the warning. The running variable is the observed tide level, measured in cm, for any given day, meaning that we do not consider the forecast

[5] Each system discriminates based on the severeness of the tide: for example, different types of sound alarms are emitted, depending on how high is the forecast tide. The systems in place, together with the MOSE barriers, already suggest that the negative effects, related to risks and damages, strongly exceed the positive ones.

[6] This approach is a non-parametric way to visualize data and identify possible jumps at the threshold. We represent the data using binned scatterplots because of the high number of points, which would make the graph hard to read if not binned. The bins are equal-sized. Each bin contains around 500 observations.

[7] This could be due to imperfect compliance or implementation, or to manipulation of the eligibility.

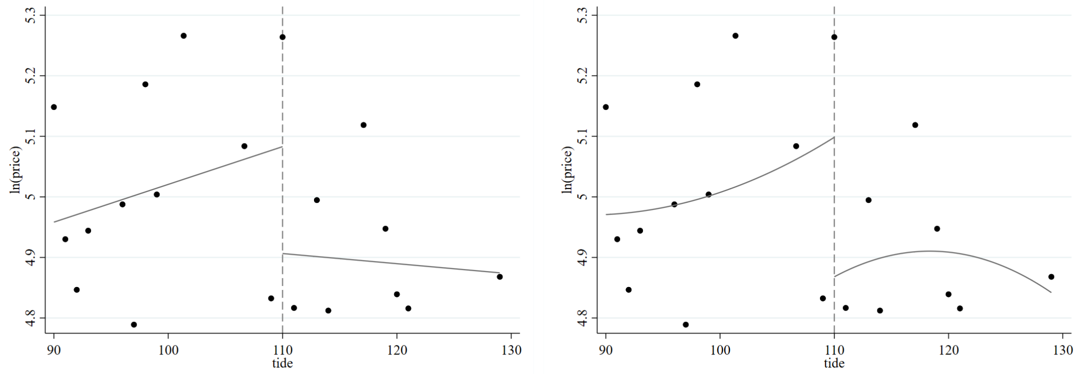

Figure 3: Binned scatterplots of the price logarithm for a double room in Venice, by tide level in the range $[90, 130]$. Each bin contains around 500 observations. The left-hand figure also reports linear fit lines below and above the 110cm threshold, while the right-hand figure reports the quadratic fit below and above the same threshold. The figure is made using the STATA `binscatter2` package by Droste (2023).

level but only the actual one.[8] As for the threshold, we consider the minimum level that activates the warning systems, that is, 110cm. As the level of the running variable passes 110cm, we expect all agents in the city to be exposed to this public and freely available information, thereby causing a downward adjustment in room prices. More precisely, not only do we expect the price to be lower for values of `tide` above 110cm, but also that a significant jump of the price appears when passing from values before and above the threshold — the so-called discontinuity.

Analytically, we can define an indicator variable $\boldsymbol{I}_t$, equal to 1 when the warning is active and equal to 0 otherwise:

$$\boldsymbol{I}_t = \begin{cases} 1 & \text{when } \texttt{tide}_t \geq 110\text{cm} \\ 0 & \text{when } \texttt{tide}_t < 110\text{cm} \end{cases} \tag{1}$$

where t represents the day and `tide` is the tide level, measured in cm.[9] As regards the availability of the information, we consider the forecast 2 days before the stay, so that the information about the tide has time to be shared and spread, allegedly influencing the market conditions and thereby prices for the day when the tide is expected. For the above reason, and in line with the visual inspection in Figure 3, we expect to observe a discontinuity in prices when passing from $\boldsymbol{I}_t = 0$ to $\boldsymbol{I}_t = 1$, namely when the alarm is triggered. The RDD analysis herein applied is aimed at measuring the statistical significance of the jump observed in the data. Differently from an OLS estimation, this approach also allows us to give a causal interpretation to the alarm since its LATE (Local

[8] Since there is no reason to expect the forecast level to be upward or downward biased, this does not impact our results.

[9] The tide is an environmental variable, and could potentially be influenced by other environmental factors, such as those in Table 3, among which the rain precipitation and wind speed, as they are determinants of the tide level increase. However, we find no discontinuity at the threshold in the data between these variables and the running variable.

Average Treatment Effect) can be measured. The baseline model is hence as follows:

$$\ln(\texttt{price}_{it}) = \alpha + \beta_1 \boldsymbol{I}_t + \beta_2 \texttt{tide}_t + \beta_3 \texttt{tide}_t \times \boldsymbol{I}_t + \boldsymbol{X}_i \boldsymbol{\gamma} + \boldsymbol{Z}_t \boldsymbol{\lambda} + \varepsilon_{it} \tag{2}$$

where $\ln(\texttt{price}_{it})$ is the price logarithm of room i at time t posted two days in advance (at $t-2$),[10] $\texttt{tide}_t$ is the tide level in cm at time t, $\boldsymbol{I}_t$ is defined in (1), the matrices $\boldsymbol{X}_i$ and $\boldsymbol{Z}_t$ are respectively a $n \times k$ and $n \times m$ matrices containing k hotel-specific and m environmental variables, used as controls, respectively reported in Table 2 and Table 3. While the cutoff is clearly set at 110cm to align with the alarm regulation, the implementation of the RDD methodology also requires the identification of a range of values around the cutoff for the running variable, which will determine the points to be used to estimate the LATE. A set of different approaches exist to compute the bandwidth (see for example Calonico et al. 2014, 2020), among which we select two approaches based on the mean square error (MSE). We consider either a common MSE-optimal bandwidth selector (MSE-common hereafter) or two different MSE-optimal bandwidth selectors, below and above the cutoff (2-MSE hereafter), which will reflect in having a symmetric bandwidth around the cutoff or an asymmetric one, respectively. The RDD methodology also requires choosing a kernel function used to weigh the points falling within the bandwidth. The kernel functions that are typically used are the uniform, the triangular, and the Epanechnikov distribution. The uniform distribution weighs all the points within the bandwidth in the same way, while the triangular and the Epanechnikov distributions give (in different ways) more weight to the points that are nearer to the cutoff. Moreover, when fitting the local linear regression using the running variable's values within the bandwidth, each weighted through the chosen kernel function, either a linear local polynomial or a higher degree local polynomial can be chosen, to account for possible curvatures.[11]

In equation (2), the main coefficient of interest is β_1, estimated using different sets of assumptions combining Epanechnikov, triangular, and uniform kernels with symmetric and asymmetric MSE-optimal bandwidth selector methods. This is done for robustness reasons, even though we expect that the asymmetric effect just before and just after the threshold applies, because of the different perceptions of risk on the two sides.

5 Results and discussion

Table 4 reports the results of equation (2) estimation as local linear regressions, with all the covariates discussed above and reporting the LATE with conventional, bias-corrected, and robust estimated coefficients for β_1. Table 4 includes several combinations of bandwidth selection methods and kernel functions (Epanechnikov, triangular) used for the estimations, applied with either first- or second-degree polynomials.[12]

The estimated coefficient for the LATE is steadily negative throughout the alternative

[10] As mentioned above, prices posted two days prior to each specific time t are included in the model to align with the moment when the alarm signal becomes available.

[11] Notice that Gelman & Imbens (2019) suggest to use only first-degree or second-degree polynomials in the RDD estimation.

[12] The supplementary material contains other combinations of bandwidth selection methods, kernel functions, and polynomials. Findings are robust, supporting the consistency of the approach. For further details on the computation, see the STATA `rdrobust` documentation and Calonico et al. (2017).

specifications, although differences in the magnitude of the effect exist. Such differences depend on the assumptions made on the bandwidth selector and the kernel type, thus reflected in different bandwidths and, consequently, different points considered in the estimation. Because of the different bandwidths applied, coefficients can not be compared across estimations. However, all coefficients are negative and statistically significant at 1%, suggesting a robust negative impact of the High Tide alarm system on the average price of accommodation in Venice in the period under investigation. The advantage of using the RDD approach allows us to identify a causal effect of the treatment (that is, the alarm activation) on the price. Our results indicate that the price drops of around 26.6 euro as a consequence of the alarm, in the most conservative of the estimations,[13] suggesting that the alarm information is processed by the price setters, thereby reducing the posted price. It is reasonable to think that this local effect is due to the alarm itself since no other variables have a jump at the cutoff.

	(1)	(2)	(3)	(4)
Conventional	-.1841	-.18422	-.64363	-1.1371
	[.03464]	[.03452]	[.03657]	[.03569]
Bias-corrected	-.18115	-.18164	-.65625	-1.2979
	[.03464]	[.03452]	[.03657]	[.03569]
Robust	-.18115	-.18164	-.65625	-1.2979
	[.03733]	[.03737]	[.04057]	[.03847]
Bandwidth type	2 MSE	2 MSE	2 MSE	2 MSE
Kernel type	Epanechnikov	Triangular	Epanechnikov	Triangular
Order local polynomial	1	1	2	2
Order bias	2	2	3	3
Observations	20181	20181	20181	20181
Left of threshold	13865	13865	13865	13865
Right of threshold	6316	6316	6316	6316
Left main bandwidth	11.180	11.270	12.870	17.298
Right main bandwidth	18.634	16.177	25.475	21.631
Effective observations (left)	2228	2228	2579	4750
Effective observations (right)	3987	3987	4455	4455

Table 4: Results from estimating equation (2) through local linear regressions, full set of covariates. Each column shows a different specification, with varying bandwidth selection methods and kernel functions. The bandwidth selection is based on the 2-MSE optimal bandwidth selector below and above the threshold (set at 110cm)
. Optimal bandwidth is calculated with the `rdrobust` package (Calonico et al. 2017). Standard errors are reported in brackets and are clustered at the hotel level. All coefficients are significant at the 1% level.

As a robustness check, we conducted a validation test of model (2) by estimating it with several alternative thresholds. We let the cutoff vary between 100cm and 120cm, with steps of 1cm, fixing the bandwidth at $\pm$10cm around the cutoff. In other words, the

[13]This is computed by applying the robust coefficient estimated in column (1) of Table 4 to the observations whose level of `tide` is between $110 - 11.180 = 98.820$ and 110.

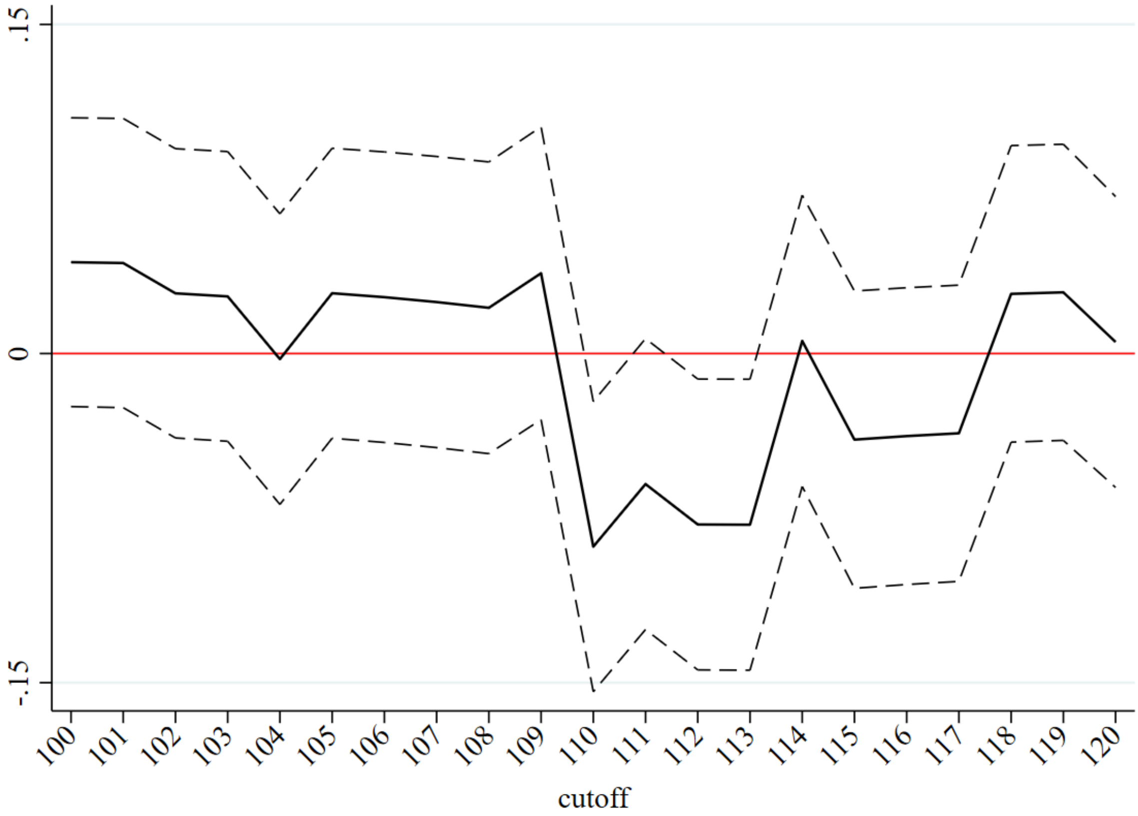

Figure 4: Validation test: sensitivity of the effect to varying tide cutoffs. Standard errors are clustered at the hotel level. We report confidence intervals at 95% level.

indicator in (1) is:

$$\boldsymbol{I}_t = \begin{cases} 1 & \text{when } \texttt{tide}_t \geq \phi \\ 0 & \text{when } \texttt{tide}_t < \phi \end{cases} \tag{3}$$

where $\phi \in [100, 120]$ with steps of 1. We keep the same bandwidth to ensure comparability of the coefficients. In Figure 4 we report the coefficients estimated together with the confidence interval at 95% for each point. We estimated the model with the full set of controls, as in (2), and reported the bias-corrected estimates, computed using Epanechnikov kernel. We can see that the statistically significant effects are found only around the actual cutoff of 110cm, and there is not statistically significant coefficient just below and just above the cutoff, confirming that is not the tide in itself, but the alarm connected with the threshold to affect prices.

5.1 Additional results

For a more general discussion, in Table 5 we report the estimated coefficients for the hotel variables included in Table 2, obtained from a standard OLS estimation of (2), with ln(`price`) as the dependent variable and the same controls used in the RDD estimation.[14] Due to space reasons, the table only displays the coefficients of the hotel variables. Environmental variables coefficients are available upon request to the authors. Our research reveals that the price of rooms located on the ground floor is, on average, 23% lower than the price of rooms located on higher floors. This aligns with previous findings in both the tourism and real estate industries, which indicate that ground-floor rooms are typically noisier and therefore less valuable (Chang & Kim 2013). Additionally, in the specific case of Venice, ground-floor rooms are more exposed to High Tide events, further contributing to their lower value.

The inspection of Table 5 also allows us to state that, consistently to the literature and intuition, rooms with stricter cancellation policies (`Nonrefundable`) tend to have lower prices. In particular, non-refundable options result in 19% lower fares (more than the market average, for which the difference between the two policies is typically around 10%). Clearly, rooms with free cancellation policy include an implicit insurance premium that covers customers from unexpected events that might occur between the booking and the departure day (Masiero et al. 2020). With regards to aesthetic and scenic values (`Withview`), rooms with a view are, on average, 23% more expensive. We also find a price premium (+34%) for rooms with a balcony (`Terrace`). These results are in line with the extensive literature on hedonic prices in the hospitality sector (Fleischer 2012, Latinopoulos 2018, Espinet et al. 2003). Independently from the presence of other characteristics, rooms described by the hotel management as of higher quality (`CatStandard` and `CatSuperior`) are associated with higher prices: according to our findings, standard and superior rooms have a 12% and 39% price premium, respectively, compared to economy rooms. In terms of overall hotel quality (`Quality`), a higher number of stars translates to an average 58% increase in prices (Espinet et al. 2003, Schamel 2012). Moreover, in accordance with research on the seasonality and price dynamics of tourism products, our study finds that rooms are 20% more expensive on the weekend than on weekdays (`Weekend`). This can be attributed to intra-week micro-seasonality, as weekends typically have a higher demand for hotel stays, especially in cultural and leisure destinations (Schamel 2012). With regards to market competition, measured as the number of available rooms of the same quality in the same neighborhood (`Competition`), a marginal increase in the degree of competition leads to a 0.5% lower price, consistently with Leoni et al. (2020) and Zekan et al. (2019). Finally, we find no statistically significant effect of the hotel inventory level (`only1room`) on the price. This is likely due to low variability, as most hotels have low availability near check-in dates. As for the type of bed (`Puredouble` and `Puretwin`), we find no significant impact on prices. In fact, it is likely that most of the quality effect is already captured by between- (`Quality`) and within- (room category) hotel-related variables.

6 Concluding remarks

In this paper, we investigate the impact of weather alerts on accommodation prices using the specific case of Venice's *Acqua Alta* phenomenon. The effect of high water signals on

[14]Notice that for the room category, we only report standard and superior categories' coefficients since the economy category is used as the baseline.

Covariate	Coeff.	t	p-value	[95% conf.	interval]
Puredouble	.03225	0.89	0.376	-.03939	.10390
	[.03634]				
Puretwin	-.09092	-0.79	0.433	-.31898	.13715
	[.11567]				
Groundfloor	-.26513***	-6.43	0.000	-.34641	-.18385
	[.04123]				
Nonrefundable	-.17554*	-1.84	0.067	-.36384	.01275
	[.09550]				
Withview	.20808***	5.14	0.000	.12823	.28794
	[.04050]				
Terrace	.28905***	3.09	0.002	.10447	.47362
	[.09362]				
Only1room	-.01610	-0.48	0.635	-.08288	.05067
	[.03387]				
CatStandard	.11240**	2.45	0.015	.02199	.20280
	[.04585]				
CatSuperior	.32725***	6.75	0.000	.23161	.42290
	[.04851]				
Weekend	.18420***	14.33	0.000	.15887	.20954
	[.01285]				
November	.31041***	13.86	0.000	.26625	.35457
	[.02240]				
Competition	-.00506***	-4.59	0.000	-.00723	-.00289
	[.00110]				
Quality	.45990***	12.27	0.000	.38602	.53379
	[.03748]				
N	20181				

Table 5: Hotel variables coefficients, OLS estimation of (2).

room fares is analyzed by merging information coming from daily prices listed by hotels on Booking.com, a popular online travel agency, with environmental and meteorological variables. We employ the regression discontinuity design approach, allowing for a causal interpretation of the effect of the alert system, which is activated by the local authorities when the water tide level is forecast to be equal to or above 110cm. Our findings reveal that, compared to similar days with non-exceptional tide levels, the activation of the high water warning system results in a significant decrease in room prices. These results are robust to alternative specifications, bandwidth selection methods, and kernel functions used in the estimation. Our findings suggest that, although some tourists may perceive *Acqua Alta* as adding a romantic trait to the city, the overall impact on tourism demand is negative. *Ceteris paribus*, compared to a day with non-exceptional water levels, hotels set lower prices, with a potentially detrimental effect on revenues.
Our work has many limitations, the most important being the unavailability of daily data on overnight stays in Venice. To the best of our knowledge, there is no readily accessible data on the exact daily number of tourists visiting Venice. This precludes us from de-

termining the extent to which weather alerts discourage tourists' visits, adding a further negative impact to the one estimated here on prices. From a theoretical standpoint, one could argue that hotels adjust their prices in response to the High Tide alerts, anticipating a drop in demand due to the natural event, and hence keeping their occupancy rate and other managerial goals unaltered. However, in a bounded rationality framework, no certainty regarding tourists' reactions to such events can be assumed, as they may show unexpected reactions to *Acqua Alta*, which could lead to sub-optimal pricing decisions. As a result, our study can provide an estimation of the reaction of suppliers to weather alerts, which indeed are triggered by demand shifts, but not an exact estimation of the total revenue loss due to high water events. Future studies should further investigate this topic.

In spite of this limitation, our work sheds additional light on the impact of high-water events on the city. Previous analyses have mainly centered on direct costs such as infrastructure and building damage and refurbishment costs, or on the indirect impact on other economic activities, such as port operations. Despite the role of the tourism sector as a key contributor to the city's economy, few studies have been conducted to assess the impact of tides on the tourism industry. Our study, therefore, makes a valuable contribution to the existing literature by providing further insights into the cost of *Acqua Alta*. Furthermore, we contribute to a more accurate calculation of the benefits (in terms of avoided potential losses for the hotel industry) associated with the implementation of protection measures, such as the MOSE barriers which – it is important to remind it – were not operational in the period under investigation. This feature presents an intriguing opportunity for future research as it enables us to evaluate the impact of the MOSE barrier implementation in terms of (avoided) price variations during *Acqua Alta* days. As the MOSE activation prevents flooding, it can be argued that the prices around the threshold should not differ anymore, not reflecting any instability in the supply and demand dynamics. We leave the test of this hypothesis, which has important policy implications, to future research.

As for the generalization of results, although the type of flooding that occurs in Venice is quite unique, thereby limiting the scope of the analysis, the applied methodology could potentially be replicated for many other relevant cases affected by different types of natural events. In our identification strategy, we give primary importance to the high tide alert and its impact on shaping local prices. Similarly, future research could adopt the same methodological framework to study the responsiveness of economic agents to signals of different climate or weather events, such as tornadoes, heatwaves, fires, or snowstorms.

As a final note, it is important to highlight that our study assumes a uniform perception of weather alerts by all economic agents, regardless of their level of exposure to the event. In other words, in the current work, we do not explicitly account for potential differences in responses of local providers based on their vulnerability to the natural hazard. Given the non-uniform elevation of the city, future studies might examine any differential reaction to weather alerts based on risk exposure, measured by the exact geographic location of the hotel, and risk adaptation, such as protective measures implemented by individual agents.

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Declaration of interest

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A Methodology used to extract information for missing dates of environmental variables

The raw data of the environmental variables reported in Table 3 had missing values for some days, that had to be estimated. In particular, some of these variables were measured at up to 3 different points within the municipality of Venice: point 1 is nearby Porto Marghera (mainland), point 2 is Campalto (city centre), while point 3 is nearby the Malamocco harbour mouth (lagoon inlet). When available, we used data from point 2, otherwise, we extracted the missing values by using the nearby point's measurement (if only one was available) or the two nearby points' measurements. To do so, we used the predicted values from the following linear regression:

$$y_t = a + \boldsymbol{W}_t\boldsymbol{\theta} + \epsilon_t \tag{4}$$

where y_t is the variable with missing values, $\boldsymbol{W}_t$ is a matrix that can have either 1 or 2 columns, depending on the availability of one or two alternative measurement points besides point number 2, and ϵ_t is the error. Once we estimate the coefficients a and $\boldsymbol{\theta}$ (that will be a 1×1 or a 2×1 vector, depending on how many columns $\boldsymbol{W}_t$ has), we use these coefficients to predict the missing values of y.
The variables for which we used this methodology are `maxSalinity`, for which we used the predictions coming from point 1 to substitute two missing values, `maxTemperature`, for which we used the predictions from points 1 and 3 to substitute two missing values, `maxTurbidity`, for which we used the predictions from points 1 and 3 to replace 37 missing values, and `maxChlorophyll`, for which we used the predictions from points 1 and 3 to substitute 29 missing values. The estimation used all the 365 days of the year under investigation (2019). The values reported in Table 3 have been computed after this substitution and only considering November and December 2019.

B Additional RDD model results

Table 6 reports a series of additional results, obtained with other combinations of assumptions concerning the bandwidth selection method, the kernel function, and the polynomials, with respect to those reported in Table 4. The LATE sign and its statistical significance are robust across combinations.

	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	-1.5475	-.64205	-.6422	-.54565	-.53991	-.54868
	[.04631]	[.03455]	[.03449]	[.03677]	[.03714]	[.03686]
Bias-corrected	-1.6646	-.66111	-.6422	-.38003	-.504	-.48936
	[.04631]	[.03455]	[.03449]	[.03677]	[.03714]	[.03686]
Robust	-1.6646	-.66111	-.6422	-.38003	-.504	-.48936
	[.06206]	[.03637]	[.03688]	[.03863]	[.04098]	[.03964]
Bandwidth type	2 MSE	MSE common	MSE common	MSE common	MSE common	MSE common
Kernel type	Uniform	Epanechnikov	Triangular	Uniform	Epanechnikov	Triangular
Order local polynomial	2	1	1	2	2	2
Order bias	3	2	2	3	3	3
Observations	20181	20181	20181	20181	20181	20181
Left of threshold	13865	13865	13865	13865	13865	13865
Right of threshold	6316	6316	6316	6316	6316	6316
Left main bandwidth	8.824	16.908	14.172	16.791	13.239	14.324
Right main bandwidth	10.836	16.908	14.172	16.791	13.239	14.324
Effective observations (left)	1431	3473	3473	3473	3063	3473
Effective observations (right)	3473	3987	3987	3987	3987	3987

Table 6: Additional results from estimating equation (2) through local linear regressions, full set of covariates. Each column shows a different specification, with varying bandwidth selection methods and kernel functions. The bandwidth selection is based either on the common-MSE or the 2-MSE optimal bandwidth selector below and above the threshold (set at 110cm). Optimal bandwidth is calculated with the `rdrobust` package (Calonico et al. 2017). Standard errors are reported in brackets and are clustered at the hotel level. All coefficients are significant at the 1% level.