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Daily deal distribution and local destination characteristics: Data-driven analysis of upmarket Italian hotel online sales practices

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ABSTRACT

This paper examines hotels' use of niche daily deal websites (flash sales) through the lens of external, destination characteristics, aiming to establish relationships between the two. Extant research indicates that both internal and external factors influence the decision-making processes of hotel businesses, yet, to date, this popular practice has been examined only from an internal business perspective. Using web scraping techniques, spatial and census data combined with quantitative analysis, the paper analyses 2741 niche daily deal offerings of 4-and 5-star Italian hotels against destination characteristics. The paper evidences the destination market structure impact on the conduct of hotels related to daily deal use. It shows that destination seasonality, economic tourist reliance, local competition and tourism demand are correlated with the volume and/or depth of discount of hotel offers featured via daily deal websites. This study contributes to the pricing research by empirically evidencing and comprehensively mapping a relationship between localised destination characteristics and hotel discounting behaviour.

1. Introduction

Environmental factors have long been recognised as critical in shaping firm behaviour (e.g. Bain, 1956; Tornatzky et al., 1990). These are subject to both local, i.e. destination and wider, national external characteristics accounted for in decision-making processes (Camisón & Forés, 2015). Hotel price adjustments and discounts are a common and frequent strategy to manage occupancy fluctuations (Croes & Semrad, 2012) often consequent of external to firm factors. Pricing strategies should be flexible, adapting to market dynamics and country-specific factors (Sánchez-Pérez et al., 2019). Daily Deals (DDs), or flash sales, have become a popular marketing and distribution channel for hotels used to address occupancy variations. Despite their prevalence in the travel market, little is known about when hotels use DDs or which types of hotels and destinations typically adopt them (Berezina et al., 2016; Geerts & Masset, 2022). As such, DDs prevail to be linked to the internal pricing strategies and thus the performance of a hotel (Berezina et al., 2016; Cassia et al., 2015), despite Tomat et al. (2019) showing that in the Mediterranean tourist-popular countries feature more DDs offers, suggesting their demand-not supply-driven use, warranting the need for further examinations. Therefore, we stipulate that mapping the localised external influences (Camisón & Forés, 2015) and regional differences (Jeon et al., 2019) in line with the DD discount behaviours identifies that DD discount engagement is related not only to the internal pricing strategies of a hotel but is used as a direct consequence of external local destination characteristics.

This paper aims to observe actual hotelier DD adoption behaviour by examining the typological structure of the hotels' environment, i.e. the market and competition conditions within the destination concerning the use of DD websites. As such the study adopts Structure-Conduct-Performance (SCP) framework as a fitting for exploring how the external environment structure influences hotel conduct (pricing strategies like DDs), which in turn impacts hotel performance in terms of occupancy and revenue generation, aspects already explored in the literature (Tian et al., 2024). The study focuses on Italy due to its strong tourist appeal, strong presence on DDs and robust, official,

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municipality-based tourism classification and statistical information system (ISTAT). Aikin to Liu et al. (2023) this study uses web scraping and publicly available official statistical data to achieve its principal goal of establishing an accurate picture of discounting adoption determinants, capturing heterogeneous effects between niche DD (nDD) engagement and external environment factors such as seasonality (Cuccia & Rizzo, 2011), tourist demand (Fernández-Morales et al., 2016), competition density (Camisón & Forés, 2015) and economic reliance on tourism (Agrusa et al., 2021). The context of this study is nDDs, i.e. higher-end travel deal websites, hence the study focuses on 4-and 5-star hotels, which are well-represented on those sites due to nDD specific business model (Budler et al., 2020; Geerts & Masset, 2022).

This study proposes that the hotel conduct, i.e. total amount of unique offers and levels of discount are used independently to address these external factors, leading to the development of dual hypotheses. It is reasoned that this approach showcases the typology of destinations whose external market structure influences the hotels to adopt nDDs. By merging the macro perspective of destination as the hotel's environmental context, we extend the available knowledge on the adoption and use of nDDs, rooting it in industrial economic and organisational theory.

2. Literature review and hypotheses development

2.1. Daily deals in the tourism

Hotels operate under two key constraints: perishable products and fixed capacity, meaning any unsold rooms result in lost profits. Revenue management has traditionally addressed this by allocating the right capacity to the right customer at the right price, time, and channel (Kimes, 1989; Kimes & Renaghan, 2011). Discounting is a common strategy, often combined with negotiating lower group or corporate rates (Xiong & Hu, 2011) and serves as a tactic to adjust supply and demand (Croes & Semrad, 2012; Sharma et al., 2023). To be effective, discounts must be distributed through the right channels, often seen as part of strategic e-marketing (Meriläinen, 2017). These channels, which these days include the proliferation of DDs, can vary in complexity and number but help customers match their needs with the hotel's offerings (Kim et al., 2009; Minor & Bratec, 2019; Minor et al., 2025).

The typical relationship between a firm and its environment is at the core of SCP framework (Bain, 1951). According to it the market structure—such as the level of competition and demand fluctuations—directly influences the conduct of firms, including their pricing strategies. Thus, for a hotel located in a particular destination, the adoption of DDs could be a direct response to market conditions (Fig. 1), e.g. as competition intensifies or tourism demand weakens, hotels might use DDs as a strategic tool to manage occupancy and optimise revenue, even if the short-term profits may be lower due to steep discounts (Minor & Bratec, 2019).

Budler et al. (2020) highlight that over time the DDs business model proliferated into 'generic' and 'niche' DDs which appeal to varied clientele driven by hedonic or utilitarian desires. Whilst the value each of those offers is different, Yi and Jai (2020) show that at least in the restaurant setting DDs serve hedonic and utilitarian purposes, and as such are effective in stimulating buying behaviour. Geerts and Masset (2022) associate nDD websites with the sale of luxury products, highlighting the challenge of balancing price perception with brand value. While Piccoli and Dev (2012) suggest that DDs can be effective for luxury hotels, Jang and Moutinho (2019) and Yang et al. (2015) emphasise the risks of luxury discounting, particularly the potential for reputational damage. This creates uncertainty for luxury hotels in determining whether, and to what extent, they should engage with DD platforms. The influence of market structure on strategic decision-making is evident, as external competitive pressures play a crucial role in shaping discounting strategies (Viglia et al., 2016). Geerts and Masset (2022) and Viglia et al. (2016) note that these pressures compel hotels to carefully assess discount depths, as excessive reductions can undermine perceived quality (Jang & Moutinho, 2019). Thus, the adoption of DD strategies by luxury hotels is not only a response to consumer perceptions but also a function of broader market dynamics, where competition and demand dictate discounting decisions. This paper seeks to explore these dynamics further.

2.1.1. Hotels and destination seasonality

Butler (1998) defines seasonality as a temporary imbalance between supply and demand in tourism, which can be measured through factors like visitor numbers, expenditure, traffic and employment. Tourism products located in destinations which are only attractive seasonally are particularly vulnerable to capital underutilisation and unstable earnings (Stojčić et al., 2022), as such the accommodation sector, with its high fixed costs, is particularly affected. DDs can help mitigate these challenges by attracting large volumes of customers (Berezina et al., 2016; Piccoli & Dev, 2012).

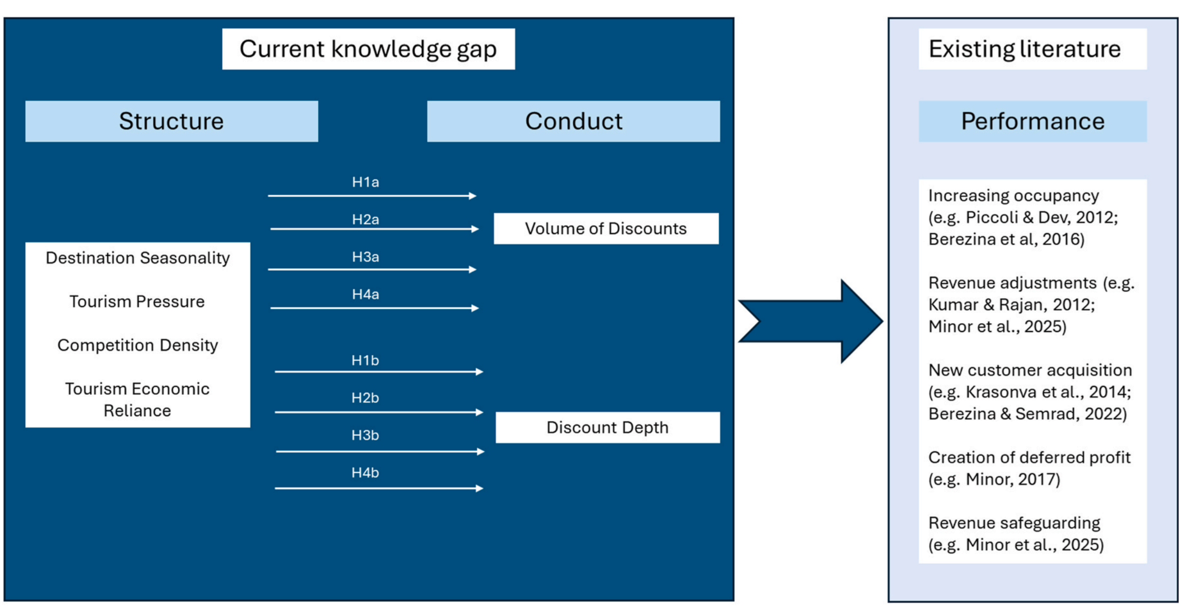

Fig. 1. Study theoretical framework.

Hotel seasonality is a multifaceted issue shaped by diverse trends, often influenced by a hotel's location, which correlates with the seasonality of the destination based on its climate (Capó Parrilla et al., 2007). For instance, sun-and-sand, urban, and winter sports destinations exhibit different visitation patterns (Sainaghi et al., 2019). Lundberg et al. (2009) observed that businesses in rural or coastal, remote areas face more severe seasonality effects, whereas city locations, with multiple attractions, can draw visitors year-round. However, even urban destinations can experience demand fluctuations due to local events (Sainaghi et al., 2019) and destinations catering to different customer types, such as cultural versus leisure tourists, will follow distinct patterns (Cuccia & Rizzo, 2011). Zhang et al. (2021) further highlight that the financial impact of seasonality varies by region, influenced by factors like dependence on specific tourist types or the predictability of demand changes.

Since most causes of seasonality are external and beyond businesses' control (Baum & Hagen, 1999), hotels often respond to occupancy fluctuations through pricing strategies. Therefore, factors like hotel location and destination type must be considered when analysing the use of DDs. Based on this, we propose the following hypothesis:

H1a. destinations that traditionally are affected by a high degree of seasonality, e.g. sun/beach or winter destinations, will record a higher number of DDs when compared to urban, city or cultural destinations.

Espinet et al. (2012) argue that under perfect competition, fluctuations in supply and demand will impact price. In destinations not heavily affected by seasonality, where supply remains steady, the accommodation sector may not need to rely on discounts. Vilchez (2013) emphasises the importance of price in understanding seasonality, suggesting that the level of discount can reflect the severity of its effects. Further, they note that destinations and accommodation types have a "tourist valuation," or a price range customers are willing to pay, therefore, DD discounts must be considered in relation to a destination's seasonal characteristics. Carlson and Kukar-Kinney (2018) note that consumers often view steep price cuts with scepticism, as it distorts their internal reference price and acceptable discount range. Similarly, Cao et al. (2018) warn that deep discounts may harm sales by creating negative perceptions of quality. Nusair et al. (2010) found a link between heavy DD discounting and lowered quality perceptions. Based on this, we propose the following hypothesis:

H1b. destinations that traditionally are affected by a high degree of seasonality, e.g. sun/beach or winter destinations, will record higher discount percentages offered on DDs when compared to urban city or cultural destinations.

2.1.2. Discounting and tourism demand

When demand is strong, hotels have little need for rate-based differentiation through discounts (Lee & Jang, 2012), particularly since using DDs to address seasonality is more about attracting custom to cover fixed costs than customer acquisition (Minor, 2017). Moreover, DDs are expensive to the business due to discount and commission and can hinder the generation of profit. Thus, DDs are often viewed as a last-resort tactic to stimulate demand. Hotels in destinations with consistently high tourist numbers may not need to engage in DDs, as they do not need to rely on discounts to attract customers. This aligns with Fernández-Morales et al. (2016), who emphasised that demand concentration helps to understand seasonal variations. Conversely, Turrión-Prats and Duro (2018) noted that in Spain, seasonality worsens with increased tourist demand. Therefore, hotels with high demand and profitability during peak seasons may not need to use DDs to protect their revenues.

Economic characteristics of peripheral areas have long been recognised as influencing seasonality and a destination's ability to manage supply and demand fluctuations (Baum & Hagen, 1999). Factors such as geographic isolation from major population centres or a lack of destination attractiveness can drive the need for discounting to attract customers. As Yang et al. (2014) highlight, hotel occupancy is harder to predict in smaller, less popular destinations, making these hotels more likely to use DDs to safeguard occupancy. Skuras et al. (2006) also note that rural tourism, while diverse, remains niche, accounting for 9.4 % of the total. Therefore, we propose the following hypotheses:

H2a. hotels located in areas of high tourist demand will record lower numbers of DDs.

H2b. hotels located in areas of high tourist demand will offer shallower discounts.

2.1.3. Discounting and the effect of competition

Kalnins (2016) linked hotel business survival and increased local competition, considering factors such as the number of hotels, their size, and pricing. In supply-saturated areas, hotels often maintain similar pricing strategies (Yup Chung, 2000) with Soler et al. (2019) showing that oversaturation in central tourist areas results in price decline. Further, hotels located in dense competition areas command higher prices, albeit in the luxury sector hotels located further apart tend to have a higher-level price point (Sánchez-Pérez et al., 2019). However, Mitra (2020) emphasises that competition in the hotel market is complex and far from perfect, leading hotels to use price and discounts as differentiation tools. Similarly, DDs can help hotels "stand out from the competition" by increasing exposure to customers (Berezina & Semrad, 2022). Offering DDs can benefit businesses both directly, through customer acquisition, and indirectly, through increased auxiliary spending (Reimers & Xie, 2018).

Enz et al. (2009) observed that some hotels use price discounting to gain market share, with the increased trade volume compensating for the cost of the deal. Karakaya and Yannopoulos (2011) found that hotel price fluctuations can have a localised effect, where a price change by one hotel triggers similar responses from competitors. Lee and Jang (2013) noted a similar effect in the case of short-term discounting, however, this applies mainly to hotels with a comparable customer base, such as upper-mid to luxury hotels (Zhao et al., 2020) which have been shown to have more stable pricing policies (Sánchez-Pérez et al., 2019). This "leader-follower" pricing strategy can be risky, as it may alter customers' price reference, making them more likely to expect and adapt to lower prices and fluctuations (Viglia et al., 2016), which is a key disadvantage of relying on DDs. Therefore, we propose the following hypotheses:

H3a. High competition in the destination will increase the number of DDs offered.

H3b. Hotels located in destinations with dense supply will offer higher discounts.

2.1.4. Discounts and tourism economic reliance

Enz et al. (2009) highlight that hotels within the same geographic area face similar external competitive and economic conditions, leading them to follow local pricing behaviours. According to Kotler (2017), the customer's perception of price is a key factor, and Viglia et al. (2016) add that this perception can be historically influenced and location-specific. Since discounting can boost demand (Melis & Piga, 2017), hotels in destinations heavily reliant on tourism may be more inclined to use discounts to stimulate demand, gain market share, and safeguard revenues (Chen et al., 2016). In markets saturated with hotels offering similar products and with a high dependence on tourism income, the need for discounted room inventory becomes more pronounced (Pearce, 2008).

Conversely, Lee and Jang (2013) note that hotels located near visitor attractions face greater challenges in maintaining steady prices and may have a higher need for discounts. This raises the question of whether hotels in peripheral destinations, with lower economic reliance on tourism, would be more or less prone to discounting:

H4a. Hotels located in destinations, which have a high economic tourism reliance, will offer more discounts.

H4b. Hotels located in destinations, which have a high economic tourism reliance, will offer deeper discounts.

3. Methodology

3.1. Data collection and sample

3.1.1. Data retrieval

Data scraping is a common method in hospitality research (Han & Anderson, 2021) used to collect hotel DD practices, extracting unstructured website data into a structured format for analysis (Sirisuriya, 2015). A custom-built tool was developed to scrape data from Verychic, a luxury hotel DD provider. Running on Linux Debian OS, the tool was coded in JavaScript and PHP (c. 1000 lines) for data classification. Appendix A contains further description of the web scraping and data collection procedure.

Once deployed, the tool collected data daily via API, accessing the Document Object Model (DOM) to retrieve the DD website's database schema and offer attributes. The API enabled stable data extraction, even under high traffic. Using Node.js, the scraped unstructured data were converted into a semi-structured format and stored in a MongoDB database, while a CRON job every 10 min grouped entries via Symfony, a PHP framework, ensuring deduplication using hashing techniques. Finally, the structured dataset was stored in MySQL for advanced querying.

The dataset included offer details (e.g., name, dates, discount size, price) and hotel attributes (e.g., provider, star rating, location, number of rooms, TripAdvisor ID). After data cleaning—removing inconsistencies and unifying hotel names—the dataset contained 11,512 unique Mediterranean offers. This study focuses on 3809 Italian DD offers from 2019, avoiding pandemic disruptions and coinciding with the availability of official, municipality-level ISTAT statistical information. Each unique DD offer represents a new promotional listing, as renewed offers are treated separately in the dataset.

3.1.2. Employing census and spatial data

In addition, the study employed official data provided by ISTAT (2022), the main producer of official economic census statistics in Italy, as well as spatial data. By combining different sources of data using geographical information, this study merged unique information with complementary data to extend the level of understanding of Italian accommodation providers embedded in the geographical and economic context of the area of reference. A spatial query was developed using QGIS software using the latitude and the longitude information of the unique offers adding the name, the statistical municipality code and the spatial layers to map all the DDs.

Finally, it has been possible to merge the unique offers database with macro indexes at the municipality level for the year 2019 such as tourism typology; tourism/economic reliance index; seasonality index; and tourism pressure, which were developed to allow for in-depth analysis of the significance of the usage of DDs by national accommodation operators. The offers without spatial information were deleted and municipalities without tourism (category I) were not used for the analysis. Appendix B details all variables used in the study and Table 1 all corresponding descriptive statistics.

3.2. Data analysis

The data analysis was conducted in STATA using two multiple linear regression models to examine relationships between key variables (Table 1) and the target variables: the number and extent of unique DD offer discounts. The first model groups nDD offers by municipality and tourism typology, while the second analyses individual nDD offers

Table 1
Study variable descriptive statistics (Source: Authors).

	Mean	Standard Error	Median	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	Confidence Level (95.0 %)
Tourism/economic reliance_index	4.39	0.02	5	0.96	0.92	2.51	−1.74	4.00	1	5.00	14,602	3323	0.03
Price	162.97	18.02	89	1071.08	1,147,213.76	943.78	28.58	38,233	34	38,267	575,456	3531	35.34
Discount	49.46	0.19	50	10.20	103.94	1.05	−0.34	84	–	84	135,804	2746	0.38
Tourism pressure	15.10	0.42	1	43.65	1905.56	105.33	7.91	1023	–	1023	163,396	10,821	0.82
Tourism Seasonality index	39.87	0.46	20	48.22	2325.34	0.56	1.12	332	–	332	431,427	10,821	0.91
Number Four_stars Hotels	61.26	4.84	8	278.94	77,806.99	2502.22	46.71	15,033	–	15,033	203,395	3320	9.49
Number Five_stars Hotels	8.80	0.45	1	26.15	683.81	1529.56	32.57	1250	–	1250	29,223	3320	0.89
Overnight amount of tourists per square Km	8042.04	222.57	134	23,152.58	536,041,815.81	29.42	4.70	298,314	–	298,314	87,022,882	10,821	436.28

across Italy. This approach tests the dual nature of four hypothesis sets—assessing both DD adoption and regional discount dynamics. Additionally, a *t*-test with equal variance was used to compare the levels of discount into different tourism destinations based on their level of seasonality, enhancing the analysis. A Variance Inflation Factor (VIF) test was conducted for both regressions to assess multicollinearity, yielding values of 3.00 and 9.00, respectively. Residuals were tested using Shapiro-Wilk W test and revealed normal distribution. Breusch-Pagan/Cook-Weisberg test was run and revealed heteroscedasticity for regression 1, but not for regression 2. Therefore, following Li (2015) we performed quantile regressions for both sets of linear regressions as well as further linear regression based only on robust residuals for regression 1, which revealed similar to the original results without heteroscedasticity present. Please refer to Appendix C outlining the results of all tests run. Based on those, we report the results of the linear regressions below.

4. Results

4.1. Descriptive statistics

Table 2 presents the study's descriptive statistics. Seaside Destinations (n = 1183) and Large Cities (n = 850) recorded the highest number of nDDs, followed by destinations with multiple tourism types (n = 371), with the top two categories comprising 56 % of the sample. These municipalities also have the highest concentration of 4- and 5-star hotels. The average discount was 49 % (SD = 2.64), indicating relatively uniform pricing across municipalities, while the average price was €183 (SD = 64.70), reflecting significant price variation. Notably, a higher Tourism Seasonality Index corresponds to greater seasonal fluctuations in tourism activity for each typology.

Out of 3809 unique nDD offers for Italy, tourism activity-related information about their location could be retrieved for 2741 unique DD offers, representing 72 % of the Italian sample. Fig. 2 shows the geographical distribution of nDD offers per tourism typology of the accommodation provider's destination.

A *t*-test (Table 3) was conducted to compare the level of discount based on tourism seasonality levels. Results show significant differences above and below the median discount level, highlighting the impact of seasonality on nDD use. To explore these differences further, a linear regression analysis was performed, as discussed in the following section.

4.2. Hypotheses testing

4.2.1. Seasonality

The results of the two multiple linear regressions served mainly to test the study hypotheses. The first regression was performed to assess the relationship between several factors that may potentially influence the extent of the adoption of such tools, measured by the number of unique nDD offers. This regression is characterised by a high R^2 of 83.9 %, therefore explaining the data set substantially. Conversely, the second regression revealed a relatively low R^2 value of 9 %. This regression is constructed by grouping all the single offers of the first regression by the Italian municipality. Although it entails a lower significance value, it is based on the data of the first regression, which has an objectively high value. Therefore, even though this regression has a lower model significance value than the first one, overall, the phenomenon can be agreeably considered to be explained by the analysis.

The first set of hypotheses modelled in this study concerned the seasonality aspect and how this may impact the number of offers per municipality, as well as according to the type of destination typically affected by seasonality. The results of the first linear regression revealed that the number of nDDs is not significantly associated with seasonality (p coefficient, 0.0163 and standard error, 0.0141; Table 4), therefore indicating that the use of nDDs is not directly associated with levels of the seasonality of destinations. Accordingly, H1a*: destinations that traditionally are affected by a high degree of seasonality,* e.g. *sun/beach or winter destinations, will record a higher number of DDs when compared to urban, city or cultural destinations*, was not confirmed through the evidence, suggesting that accommodation providers do not use nDDs (in terms of numbers of nDD offers issued) as a way to offset seasonality.

As for the level of nDD discount, the second linear regression (Table 4) shows that higher discounts were associated with municipalities with two or more tourism types, while large city providers have higher discounts than providers in historical destinations. Further, while lake destinations adopt lower discounts but still employ a heavy number of nDDs, thermal tourism providers adopt higher discounts. Generally, higher levels of nDD discounts were found in municipalities that are connected to tourism. Overall, the evidence shows that nDDs measured by the discount extent are a way to tackle seasonality, extending Berezina and Semrad (2015), i.e. the bigger the seasonality within the destination, the larger the discount recorded, therefore confirming the second hypothesis; H1b*: destinations which traditionally are affected by a high degree of seasonality,* e.g.*, sun/beach or winter destinations will record higher discount percentages offered on DDs when compared to urban city or*

Table 2
Characteristics of DDs adoption by tourism typology area (Source: Authors).

Tourism Typology	Number of Daily Deals	Daily Deals Distribution	Average of advertised Discount	Discount standard deviation	Average Price (€)	Price standard deviation	Total overnight stays	Number of five-star Hotels (municipality)	Number of four-star Hotels (municipality)	Tourism Seasonality Index
Large Cities	950	24,94 %	48 %	9,808,457	189	1,624,954	15.387.734.825	25	170	20
Municipality without a tourism category	346	9,08 %	50 %	9,876,397	144	2,964,517	9.019.343	16	221	58
Cultural Destinations	358	9,40 %	48 %	9,969,756	303	2.247,43	69.499.002	211	1	58
Lake Destinations	180	4,73 %	44 %	8,723,379	169	122,397	43.095.913	37	328	76
Mountain Destinations	283	7,43 %	46 %	1,142,551	264	6,871,725	56.803.063	66	922	76
Seaside Destinations	1.183	31,06 %	51 %	1,009,188	188	2,006,174	617.294.115	2	12	94
Spa Destinations	133	3,49 %	52 %	9,695,624	132	6,714,567	49.898.074	180	672	48
Two or more tourism typology	371	9,74 %	52 %	9,907,403	187	1,745,293	191.149.605	345	3	70
Total/Average	3.809	100,00 %	49 %		183		16.424.493.940	28	188	62

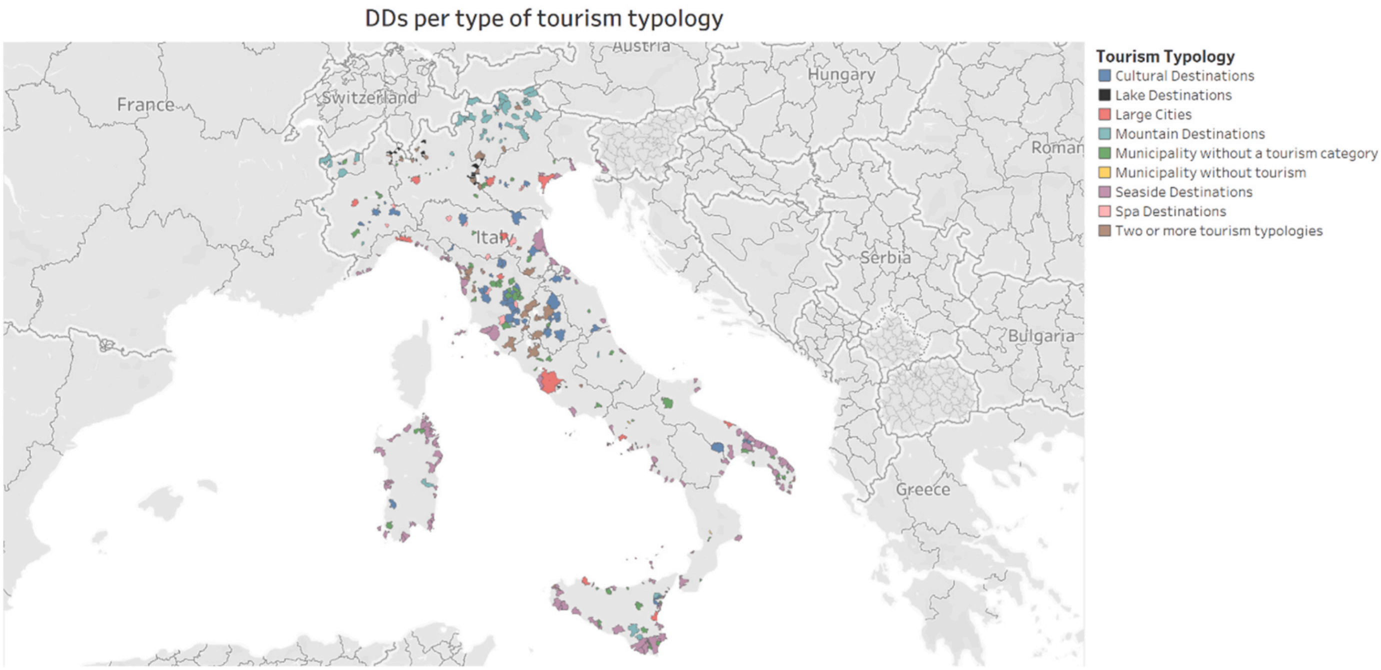

Fig. 2. Geographical map of nDDs distribution per tourism typology (source: Authors).

Table 3
T-test: accommodation providers, level of discount and seasonality (Source: Authors).

. Ttest Discount, by(Seasonalityindex_group)						
Two-sample *t*-test with qual variances						
Group	Obs	Mean	Std.Err.	Std.Dev.	[95 %Conf. Interval]	
1	1356	50.12684	0.2728864	10.04874	49.59152	50.66217
2	1385	49.01227	0.2633557	9.800937	48.49565	49.52889
Combined	2741	49.56366	0.1898236	9.938132	49.19145	49.93587
diff		1.114569	0.3791401		0.3711397	1.857999
diff = mean(1) -mean (2)					t =	2.9397
H0: diff = 0				Degrees of freedom =		2739
Ha: diss <0		Ha: diff ! = 0			Ha: diff >0	
Pr(T < t) = 0.9983		Pr(ITI > ItI) = 0.0033			Pr(T > t) = 0.0017	

cultural destinations.

4.2.2. Tourism demand

Regarding the hypotheses concerning tourism demand, i.e. the popularity of a given destination and the use of nDDs, this study refers to tourism demand using the proxy indicator of tourism pressure, defined as the total overnight stays per inhabitant in the municipality of the provider. The first linear regression (Table 4) reveals that more intense use of nDDs is linked to a decrease in tourism pressure. This indicates and reinforces the use of nDDs as a tool to offset a decrease in demand, namely a reduction of presence in the associated destination and therefore demand for accommodation (p coefficient, −0.0341; standard error, 0.00934). Therefore, H2a*: hotels located in areas of high tourist demand will record lower numbers of DDs* is confirmed.

The second associated hypothesis that concerns the level of nDD discount states H2b*: hotels located in areas of high tourist demand will offer shallower discounts*. The linear regression shows results in line with the previous hypothesis (p coefficient −0.0171; standard error 0.005, Table 4), therefore confirming the H2b; hotels located in areas of high tourist demand will offer shallower discounts hypothesis. The relationship between tourism pressure and nDD discount levels is significant but negative, therefore, nDD discounts are generally higher when the tourism pressure diminishes.

4.2.3. Destination competitiveness

The third set of hypotheses concerned competition levels at the destination of the accommodation provider and the adoption of nDDs. In this study, the competition was assessed via the inclusion of the number of four and five-star hotel establishments per single municipality as dependent variables of the regressions (Table 4). The first regression reveals a positive relationship between market competitiveness and the use of nDDs for both four and five-star hotels located in competitive destinations; however, five-star hotels show a stronger relationship than their counterparts. Therefore, H3a*: High competition in the destination will increase the number of DDs offered is confirmed.*

In terms of the level of discounts offered, the second regression shows that the bigger the presence of four-star hotels, the higher the discount of the nDDs is (p coefficient 0.0791; standard error 0.014, Table 4); and conversely, a bigger discount occurs when there is less competition between 5-star hotels, with the latter value being relatively low and therefore not particularly influential in the model. Therefore, H3b*: Hotels located in destinations with dense supply will offer higher discounts* is also confirmed, but only for 4 and 5-star hotels.

Table 4
Results of linear regressions 1 and 2 (Coefficient and Std. Error values) (Source: Authors).

VARIABLES	(1) DDs_per_municipality	VARIABLES	(2) Discount
Two or more tourism typologies [1]	−11.406*** (7.783)	Two or more tourism typologies [1]	3.564*** (0.927)
Cultural Destinations [2]	−12.487*** (7.683)	Cultural Destinations [2]	−1.143 (0.973)
Seaside Destinations [3]	−14.786*** (7.670)	Seaside Destinations [3]	1.542* (0.860)
Mountain Destinations [4]	−11.813*** 7.747	Mountain Destinations [4]	(1.183) (1.231)
Lake destinations [7]	−9.143** 7.918	Lake destinations [7]	−5.278*** (1.234)
Spa Destination [8]	−10.701** 7.953	Spa Destination [8]	3.768*** (1.185)
Municipality without a tourism category [9]	−13.814*** 7.674	Municipality without a tourism category [9]	1.093 (1.093)
1 Tourism economic index (very low reliance)	0.110 2.279	1 Tourism economic index (very low reliance)	1.075 (1.397)
2 Tourism economic index (low reliance)	−0.470 1.235	2 Tourism economic index (low reliance)	−0.083 (1.070)
3 Tourism economic index (medium reliance)	−0.806 1.466	3 Tourism economic index (medium reliance)	3.155*** (0.802)
4 Tourism economic index (high reliance)	−0.566 1.342	4 Tourism economic index (high reliance)	2.630*** (0.568)
Tourism_Seasonality	0.0163 (0.0102)	Tourism_Seasonality	0.0337*** (0.007)
Tourism_pressure	−0.0341*** (0.00867)	Tourism_pressure	−0.0171*** (0.005)
Four_stars_Hotels	0.454*** (0.127)	Four_stars_Hotels	0.0791*** (0.014)
Five_stars_Hotels	2.575*** (0.817)	Five_stars_Hotels	−0.504*** (0.100)
Overnights per square km	−0.000*** (0.000)	Overnights per square km	0.000*** (6.730)
Discount	0.132*** (0.0373)		
Price	−0.0003 (0.000)		
Constant	10.053** 7.933	Constant	46.63*** (0.635)
Observations	359	Observations	2.724
R-squared	0.839	R-squared	0.09

Standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

4.2.4. *Tourism economic reliance*

The last set of hypotheses relates to the reliance on tourism activities of destinations and includes measurements based on the incidence of employment in the tourism and culture sectors at the different destinations. Interestingly, the first regression (Table 4) reveals the existence of no relationship between economic dependency on tourism and the number of nDDs, therefore rejecting H4a*: Hotels located in destinations that have a high economic tourism reliance will offer more discounts*.

Conversely, the second regression highlights the positive relationship between the economic dependency of a municipality and the level of nDD discounts in municipalities that are connected to tourism (Table 4), confirming H4b*: Hotels located in destinations that have a high economic tourism reliance will offer deeper discounts*.

5. Discussion and conclusions

5.1. *Discussion*

The results show that when the hotels use nDD as a means to offset seasonality, they only do so by manipulating the depth of discount but not the volume of offers. When compared to our base, i.e. Large City destinations, destinations that struggle with seasonality are more likely to offer deeper discounts, thus confirming this particular trait in the use of DDs. However, there is no noted difference in the volume of DD between the destinations affected and those unaffected by seasonality. Therefore, our findings suggest that DDs are used as a stable and permanent distribution channel, not a one-off use platform. They are used flexibly to adjust discount rates to offset seasonality. This confirms the conclusions of Budler et al. (2020) concerning the use of niche DDs as a part of the distribution channel mix, and not merely as an ad-hoc promotion method.

Examining the destination typology and seasonality index further, deeper discounts, again compared to the base of Large Cities, are found in: municipalities with two or more tourism types; maritime/seaside destinations; thermal tourism destinations; or with no specific tourism type. This leaves mountain, lake and cultural/historical destinations less likely to heavily discount, suggesting these destinations can attract customers with alternative offerings out of season. The opposite findings relating to spa and cultural destinations contrast with Cuccia and Rizzo (2011) who note discounting is less pronounced in areas characterised by specific customer types. This finding therefore suggests that nDD use is location but not seasonality-specific per se, extending the findings of previous research to nDD context (e.g. Sainaghi et al., 2019) and thus questioning the established function of DDs as a distribution channel whose key attribute has been long associated with its power to mitigate the effects of seasonality (Berezina & Semrad, 2015) following the 'needs-based' distribution channel logic (Pearce, 2008).

Our results evidence a relationship between the concentration and variations of tourism demand and nDD availability found in a given destination, thus supporting the work of Fernández-Morales et al. (2016). Additionally, the results extend Yang et al. (2014) findings which showed that hotels located in low-tourist demand locations offer more deals and deeper discounts. This provides new evidence of the specific effect of nDDs use and indicates them to be a tool to simulate location-based demand. Equally, most of the nDD offers are noted in Large Cities categories, areas of high tourism pressure that, however, record shallow discounts. This use of nDDs reminisces the traditional use of discounting (Lee & Jang, 2013) and points to nDDs being used as a management tool designed to address the specific circumstances of the wider destination-specific business environment the hotel operates in, in opposition to its organisational environment reflected in its performance alone.

Further, our findings clearly show a localised effect of nDD discounting, extending the work of Karakaya and Yannopoulos (2011), who postulated that in areas of high competition, DD discounting, in terms of the number of deals offered, is more commonly applied. Our findings confirm that this is true for both 4 and 5-star hotels, evidencing that nDDs are a viable distribution strategy even on the luxury end of the hotel spectrum; this further supports observations by Budler et al. (2020) of the inclusion of the DD within the permanent distribution channel mix. However, the application of the discount is the point of differentiation and thus shows the true localisation effect on the use of nDDs. Namely, the discount increases in line with the density of 4-star hotels per inhabitant but decreases with 5-star providers' presence. This leads to several observations; since there are more 4-star hotels operating on the market, to gain a competitive advantage (Enz et al., 2009) the hotel may be more likely to utilise nDDs websites as a way of accessing the specific market. Equally, in areas of high competition, 5-star luxury establishments are less prone to offer deep discounts, even on more 'exclusive' nDD websites. The lack of discount proneness is likely due to reputational ramifications in the 5-star segment (e.g. Jang & Moutinho, 2019) which outweigh the quest for competitive advantage. Namely, the deepness of the discount may be a signal of inferior quality, thus instead of gaining, losing market share. Only in destinations of low 5-star competition, our data show deeper discounts applied. This is particularly significant, as it can expose the hotels to a greater risk of changes in price reference points where the customers adapt to the lower price over time (Viglia et al., 2016). This discounting approach might be explained by external destination factors, which are not per se aligned with the expectations of 5-star guests.

The last sets of results signal that hotels in areas of high economic tourism reliance use nDD websites, but the number of offers featured is no different than in areas of low tourism reliance. This signals that the decision to engage or not with the DDs channel is influenced by other aforenoted external, destination characteristics such as competition and internal, organisational factors such as financial stability. The point of differentiation, however, is the level of discount applied, with the hotels located in high economic tourism reliance areas offering deeper discounts, signalling a concession-based not quantity-led strategy of nDD sales. This may signal clearance-like (Nakhata & Kuo, 2013) use of the websites to address problems with distressed inventory (e.g. Berezina et al., 2016) and point to the destination factors external to the hotel as the ones stimulating more aggressive discounting strategies.

5.2. Theoretical and practical implications

This study contributes to the growing extant knowledge derived from utilising machine learning to assess and establish spatial distributions of regional tourism patterns. As such, similarly to Morales-Pérez et al. (2024), it empirically records the spatial distribution of nDD offers to showcase patterns and hubs of adoption but expands this by accounting for tourism dimensions of the local municipalities. It contextualises findings with the use of publicly available secondary data to showcase the heterogeneous effect of external, regional tourism environment and thus building a robust picture of the market structure (S) in relation to the use of nDDs (P) (Liu et al., 2023) within the quest for improved hotel performance (P).

Further, by incorporating SCP framework we provide a link between market conditions and hotels' nDD usage strategies, thus moving beyond firm-centric literature perspectives. This represents the first study to systematically identify the external factors that contribute to the use of DDs as a distribution channel, reinforcing the notion that discounting strategies are not solely a function of internal revenue management practices but are contextually adapted to macro-environmental conditions. Specifically, we show that nDDs serve as a dynamic and flexible mechanism, wherein hotels adjust the depth of discounts, volume of offers, or a combination of both, to counteract external pressures. As such our study contributes by identifying distinct patterns of nDD usage linked to seasonality, economic reliance on tourism, local demand fluctuations, and competition intensity. Namely, we evidence that highly seasonal destinations tend to mitigate demand volatility by increasing discount depths rather than volume, reaffirming DDs as an adaptive pricing tool rather than a temporary crisis-management solution. We confirm that hotels in high tourism-reliant economies employ deeper discounts, thus illustrating a dependence on aggressive pricing strategies to maintain competitiveness. In highly competitive markets, 4-star hotels respond with both a higher volume of DDs and deeper discounts, whereas 5-star hotels demonstrate an inverse trend, offering fewer discounts in dense competitive environments to preserve brand integrity. This supports the broader pricing literature, evidencing how competition affects price elasticity differently across market segments. Lastly, hotels in high tourism-demand destinations exhibit lower DD adoption and shallower discounts, aligning with demand-driven pricing logic, where strong visitor inflows negate the necessity of steep price reductions.

These insights contribute to price management literature by contextualising competitive pricing strategies within local market structures, showing how geographical and economic determinants shape nDD adoption and discounting behaviour. This has critical implications for destination-based competitive pricing theories, particularly in luxury markets, where price sensitivity and exclusivity trade-offs must be carefully managed. As such, we show leader-follower behaviour in the nDD behaviour; if a hotel is located in a municipality with a high number of daily deals, they need to follow discounting trends to elicit a change in competitors' discounting behaviour.

From a practical perspective and in line with SCP logic, we show that nDD adoption challenge lies in balancing pricing flexibility with brand positioning, since the engagement is not purely an internal strategic choice, but a reactive decision to external environmental conditions. Revenue managers can use this knowledge to predict competitive pricing responses and proactively adjust their DD strategies in line with market pressures. Crucially, this study evidences that discount depth and volume are employed as independent strategies, enabling destination-specific adaptations. This flexibility allows hotel managers to better align their pricing approaches with local market conditions, mitigating the risks of price erosion while maintaining competitive positioning within the luxury and upmarket hospitality segments. Beyond hotels, nDD operators can refine their targeting strategies—specifically, focusing on 5-star hotels in low-competition markets to secure deeper discounts, while approaching 4-star hotels in high-competition zones for higher volume deals.

5.3. Limitations and avenues for future research

As this study focused on Italy, results may differ in less tourism-developed countries. Future research should explore nDD usage in such contexts or across broader geographical regions to enhance generalisability. Additionally, this study adopted a holistic approach, using overnight stays per inhabitant as a proxy for tourism pressure. Alternative measures may yield different results, warranting validation in future studies. Moreover, multiple concurrent destination characteristics—such as large cities, mountain destinations, and tourism economic reliance—may influence discounting strategies differently. Competitive pressures, market structure, and external economic conditions also play a role in shaping pricing decisions. Thus, future research should employ multivariate analyses to examine nDD deal volume and discount levels against multiple external factors, ensuring a more comprehensive understanding of discounting behaviour in varying market conditions. Finally, our study relied on two main sets of data to enable the relationships to emerge, namely the data collected from the DD booking platform and the official ISTAT statistical information per municipality. Due to delays in the publication of the official statistics and the exclusion of the pandemic period, the paper derives from 2019 data. Any future studies should therefore use post-pandemic recorded datasets to build upon this work.

CRediT authorship contribution statement

Katarzyna Minor: Writing – review & editing, Writing – original draft, Resources, Project administration, Investigation, Conceptualization. **Dario Bertocchi:** Software, Methodology, Investigation, Formal analysis, Conceptualization. **Giancarlo Fedeli:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Luka Tomat:** Writing – review & editing, Methodology, Formal analysis, Data curation. **Miha Bratec:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization.

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Appendix A. Data retrieval additional explanation

To collect hotel Niche Daily Deal (nDD) practices, a data scraping tool was used. We provide additional information about the scraping tool and processes employed to supplement the explanation provided in the paper.

A custom-built tool was developed to scrape data from Verychic, a luxury hotel DD provider. Running on Linux Debian OS, the tool was coded in JavaScript and PHP (c. 1000 lines) for data classification.

The tool ran once a day at 2 a.m. and parsed all relevant data. It works by firstly automatically logging into the target website and then executing predefined tasks. Initially, the scraping tool retrieved offers URL links, from which it read DOM elements, which enabled the determination of common classes. This way, the scraping tool obtained the relevant data of individual offers, such as URLs, offer names, start and end dates, discount size, original and reduced price, price types, provider names, star rating, address, city, country, longitude, latitude, number of rooms, and TripAdvisor IDs. The data was subsequently stored as raw, unstructured data in the form of objects within arrays.

Since the targeted website has used a traditional front-end and back-end structure, where the back-end provided data to the front-end via an API, this API has been utilised to retrieve structured data schematics, which eliminated the need for extensive HTML scraping.

Once the data was collected, it was processed and structured. The scraping tool used a JavaScript runtime library, Node.js, to handle the extraction and transfer of data into a MongoDB database, where it was stored in a semi-structured format. At scheduled intervals, a tool (written in PHP utilising the Symfony framework) retrieved records from MongoDB, grouped them by entities and attributes, and processed them into a fully structured format. This refined data was then stored in a MySQL database for further use.

Appendix B. Study variable specification (Source: Authors)

Variable name	Description	Source
Tourism Typology	Identified mainly based on geographical (proximity to the sea, altitude, etc.) and anthropic (large urban municipalities) attributes. The identification of the prevailing tourist category is linked to the presence of minimum conditions regarding tourist overnight stays. 9 tourism categories were identified: A. Large Cities [10], B. Cultural Destinations [2], C. Lake Destinations [7], D. Mountain Destinations [4], E. Seaside Destinations [3], F. Spa Destinations [8], G. Two or more tourism typologies [1], H. Municipality without a tourism category [9], I. Municipality without tourism (not considered for this study).	ISTAT
Tourism/Economic Reliance Index	Represents the economic variables that belong to the Italian Economic Activities Classification (ATECO) sectors related to tourism. These are based on the incidence of employment in the tourism and culture sectors, the added value per capita imputable to the tourism and culture sectors, and finally the location ratio of tourism and culture local units. Measured on a 1 (very low reliance) - 5 (very high reliance) scale based on quintiles distribution.	ISTAT
Tourism Seasonality	Coefficient of variation of total monthly overnight stays applying the standard deviation of monthly overnight stays/average*100. A higher value of the tourism seasonality Index corresponds to a concentration of tourist overnight stays in a certain period of the year (e. g., Rome has a value of 19,55 while Rimini has a value of 100,46).	Developed by the authors per single municipality using 5 years of monthly data (2015–2019) following ISTAT methodology.
Tourism pressure	Total overnight stays per inhabitant.	Developed by the authors per single municipality following ISTAT methodology.
Overnights per square km	Overnight amount of tourists per square kilometre. Total number of the year overnight tourists stays per square km in all types of accommodation (control variable).	ISTAT
Number of Four stars Hotels	Number of 4-star hotel establishments per single municipality (year 2019).	ISTAT

(continued on next page)

(*continued*)

Variable name	Description	Source
Number of Five stars Hotels	Number of 5-star hotel establishments per single municipality (year 2019).	ISTAT
Price	Final price of a daily deal offer.	Unique offers database
Discount	Discount rate of the daily deal offer.	Unique offers database

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhtm.2025.03.013.

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