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ORIGINAL RESEARCH

As time goes by: last minute momentum booking and the planned vacation process

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Abstract

"Last-minute" deals in travel and tourism services are very appealing not only to travellers but also for service providers. Timing and price are central to an optimization strategy for last-minute deals for both sides. This study analyses last-minute timing behaviour for self-catering customers and proposes to the supplier an estimation of the critical *last-minute momentum* (LMM) that is, the optimal moment for launching these kinds of deals. The data emanates from the largest self-catering accommodation booking platform in the *Romand* Valais in Switzerland, containing more than 154,000 transactions. The study focuses on the domestic market, that is the largest market of the platform consisting of more than 90,000 transactions. The results show that LMM estimation accuracy increases when the party composition is considered even though improvements are not homogeneous across seasons. For practitioners, the results clarify the timing optimization of last-minute campaigns. For scholars, the results demonstrate that last-minute behavior challenges traditional paradigms of the planning vacation process (PVP). This is an extended version of a conference paper entitled "When last-minute is really last minute" previously published in the proceedings of the Information and Communication Technologies in Tourism 2018: Proceedings of the International Conference (ENTER 2018) held in Jönköping, Sweden, January 24–26,

Keywords Last minute · Big data · Survival methods · Kaplan–Meier survival function · Planning Vacation Process (PVP)

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1 Introduction

The perishable nature of travel and tourism services is one of the principal drivers for suppliers to offer last-minute deals. These deals offer lower prices than initially proposed, but for travellers there is a certain subjective dimension of perception of last-minute deals. For providers, as discounted prices should boost customer demand, the aim of last-minute promotions is to sell out the late-availability capacity which could remain otherwise unsold without any loss of revenues by launching them at an optimum timing (Scaglione et al. 2017; Sirakaya and Woodside 2005). It has been established that the existence of last-minute deals and the opportunistic nature of vacationers can result in consumers making changes in their vacation planning process, and in suppliers offering early booking inducements or last-minute discounts (Decrop 2010).

Specifically looking at the accommodation market, other strategies besides last-minute deals have been used based on the trade-off between prices and timing. Those techniques are flash sales (or daily deals), private sales or online coupons (Berezina et al. 2016). Timing is gaining more and more importance as online booking activities increase, as the Internet reduces the information gap between accommodation providers and travelers. This allows travelers the possibility to continue researching data up to the time when they perceive the best deal to be made (Chen and Schwartz 2008; Song et al. 2017; Webb 2016).

This research project is innovative and important. Analysing actual big data, the project seeks to answer fundamental questions that will be of significant importance and use for the travel and tourism sector. The research focuses on the last-minute timing in the case of self-catering accommodation in the region of the *Romand* Valais in Switzerland by exploiting a data base containing more than 154,000 transactions for 19 different destinations and origin countries. This research will focus on the domestic market, namely Swiss resident customers. The main aim is to estimate the momentum for launching last-minute sales by answering the following questions: how many days (on average) before a given date does the share of bookings already received represent 95% of the total number of bookings expected? Does the inclusion of the composition of the party improve seasonal LMM estimates?

This research analyses the booking period (BP) as the dependent variable, namely the time lapse between the booking and the actual arrival date. BP span could be modelled as the *length of life* of booking transactions: its birth is the booking date and the end of its life is the arrival date. Hence, Kaplan–Meier (KM) survival models is an appropriate strategy to find these estimates.

The paper is organized in the following way: following this introduction, the literature review discusses last-minute booking from the point of view of supply and demand. The third section discusses the research question. The fourth section contains the description of the data and methodology and sampling methods used on big data. The fifth section analyses the results. The final section discusses the results in terms of theoretical and management dimensions and implications for future research.

2 Literature review

This review of the literature will evaluate studies especially in relation to last minute bookings: from the demand side these will include references to "deal seekers". From the supply side studies, there is an emphasis on revenue management studies and the development of fence rates. Fence rates are rules or restrictions placed on customers to facilitate customer segmentation that may be based on their needs, ability to pay or behavior.

The extant literature on last minute booking has often been in relation to hotel accommodation (Chen and Schwartz 2008; Chen and Schwartz 2013; Chen et al. 2011). This is often related to dynamic pricing and revenue management and price optimization models (Abrate et al. 2011; Abrate and Viglia 2016).

There have been recent studies on last minute booking and mobile applications for hotel reservations, especially in relation to improved operating performance in the hotel sector (Makki et al. 2016). Studies on related tourism sectors include airline reservations (Koenigsberg et al. 2008). Tourism marketing strategies have been researched from the viewpoint of prospect theory, whereby framing is used to effectively persuade tourists to book in advance (Rahman et al. 2018). The possibility of booking discounted accommodation and flights by consumers, and the opportunity to fill otherwise vacant hotel rooms and airlines seats appears to be a "win–win" situation (Marin-Pantelescu 2016). Relatively little attention, however, has been given to the self-catering accommodation sector in terms of last minute promotions.

2.1 Last minute bookings from the demand side

Recently last-minute promotions have grown exponentially due to advances and developments in Information Communication Technology (ICT). This has led to the growth of an increasingly sophisticated consumer segment that may be classified as *deal-seekers*. This segment is becoming more and more knowledgeable to the point that they are challenging companies' revenue management (RM) strategies (Chen and Schwartz 2008). There is a perceived wisdom that business travellers are less price sensitive and tend to book nearer to the travel date whereas leisure travellers are willing to book early if they believe that they are getting the best deal (Chen and Schwartz 2008; Koenigsberg et al. 2008.)

Deal seekers Basically search and book online with low willingness to pay and invest high amount of efforts and time in comparing different brands. Their strategy is to book the travel product or service at the optimal time, when the price is lowest. The tension between the likelihood of having a better deal later and the risk of not being able to book because the accommodation is sold out characterizes deal seekers' booking processes. Moreover, the strength of these two elements of expectation and risk change over time (Chen and Schwartz 2013). Thus, consumers show adaptive expectations, meaning that they not only rely on the recent revealed providers' information but adjust new information to past experiences (Liu and van Ryzin 2011). The perception of gaining last-minute deals by the customers and the willingness to pay may depend on subjective factors that could be "susceptible to outside manipulation" (Chen and Schwartz 2013, p. 18). It has been suggested that asymmetric information situated between providers and customers is the best revenue management policy to offer last-minute deals for the firms (Koenigsberg et al. 2008).

The "culture" of deal-seekers not only challenges revenue management strategies as prices could be driven even lower, especially in low-demand periods (Webb 2016), but this segment is also increasingly learning "to anticipate price changes, especially last minute deals, and modify their behaviour based on […] expectations" of lower prices (Chen and Schwartz 2013, p. 10). Some mathematical models from the operations management literature (for example in fashion and products) tackle these learning and expectation formation aspects. Blattberg et al. (1995) produced a seminal study that analysed the use of sales promotions. Liu and van Ryzin (2011) examined the use of firm's discounting strategies in relation to customers' learning speed and risk aversion. Specifically concerning tourism in Switzerland, Falk and Scaglione (2018) examined ski lift tickets and discounts affecting behaviour in local tourism demand.

Advance selling is the other side of the last-minute coin: it refers to the purchasing of the services in advance of the consumption period and the requirement is the uncertainty about the availability and future value of the product or services. For the buyer, besides the reduction level of uncertainty, he/she expects some benefit from this advance purchase (Berezina et al. 2016).

Last-minute behaviour seems to be poorly described by traditional PVP models (Dunne et al. 2011; Sirakaya and Woodside 2005). As an example, the three-stages PVP models comprises: need recognition, search for destination, and evaluation of destination-related choices (Moutinho 1987). This does not explain certain kinds of vacations which are opportunist in nature, such as city break vacations that are similar to last-minute ones. In these cases, the characteristics of travel party, duration, distance and date flexibility could be more important than the destination itself (Dunne et al. 2011; Sirakaya and Woodside 2005). Nevertheless, late bookings should not be considered as purely impulse or emotional buying as much as early bookings also should not be considered as rational or prepared trips. They both are also influenced by practical and social constraints (Decrop and Snelders 2004).

2.2 Last minute bookings from the supply side

Revenue management is the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right price at the right time (Kimes and Wirtz 2003, p. 125). In airlines, last-minute deals aim to attract the more price-conscious of the tourism segment that did not purchase tickets within the regular period with deals that are often offered very close to the actual flight day (Koenigsberg et al. 2008).

Last-minute (LM) deals are part of revenue management strategies that use the lever of pricing discrimination. Technically speaking, price discrimination exists when "the same, or similar, goods or services are sold to different customers, or customer segments, at different prices": these applications lead to the development of fence rates (Song et al. 2017, p. 1). The pricing discrimination could be based on a physical basis such as airline class of travel or a nonphysical basis such as the timing of reservations. Last-minute deals obviously belong to the latter case (Kimes and Wirtz 2003; Song et al. 2017).

Cancelation policies play a role in the propensity to book. If the company pursues an aggressive cancelation policy by demanding high fees, it reduces the propensity of booking and also encourages the customer to continue searching (Webb 2016). In the case of last-minute booking, an aggressive policy of high fees prevents high-level costs especially when there is not enough time before the date of stay to sell the room to another customer (Chen et al. 2011).

As pointed out above, RM is the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right price at the right time. This research will focus on the optimum moment to launch last-minutes deals in the case of self-catering accommodation for the C.I.T.I. platform providers. This will be more fully described in Section. 4.1

3 Research questions

The literature review shows that last-minute behaviours are sophisticated and in a continuous learning process and are not simply emotional impulses, Chen et al. (2011) and Chen and Schwartz (2013). Last minute booking behaviours have been seen as expressing a preference for a certain season and from a certain country of origin, but there may be other, possibly more important factors at play including party composition and length of stay. In addition, the destination could be fixed much later than described in the traditional planning vacation process (PVP) models as it is a secondary aspect in the planning process, Dunne et al. (2011) and Sirakaya and Woodside (2005).

Customers are participating in a learning process that smooths the tension between risk of scarcity, with for example, the possibility of accommodation provider selling out, balanced with the expectation of a better deal. As has been seen from the literature, customers (especially deal-seekers) have increasingly sophisticated strategies. From this view-point, for providers, a better understanding of demand in general and of deals-seekers in particular is central. Considered crucial would be the optimal moment to launch last-minute deals.

An earlier study (Scaglione et al. 2017) focused on the estimates of the median (50% percentile) of the booking period (BP) on the segmentation based on country of origin and season. This research project estimated, in place of the median, the 95% percentile of that distribution, that is the average number of days before any arrival date where the share of the bookings already arrived at is 95% of the total expected. From hereafter, the 95% percentile will be referred to as the critical *last-minute momentum* (LMM) and the bookings arriving before the given date will be referred as the *bookings in hand.*

Though the results of the earlier study (Scaglione et al. 2017) on the median BP time yielded satisfactory results, those of this project were somewhat disappointing. The segmentation based on origin/season that yielded satisfactory estimations of the median time of booking period (Scaglione et al. 2017) failed in the case of 95% percentile estimation. However, this project, using a logistic model show that other independent variables other than seasonal/country are significant in characterization of LM transactions, such as party composition, destination and length of stay. The results of these models are available at: https://www.tourobs.ch/5700.aspx.

The focus of this research was on domestic tourism demand, which is the first market of the data under study, and its aim was to find the estimation of *critical last-minute momentum* (LMM) for each combination season and party composition (single/couple, 3 to 7 persons and more than 8 persons).

Research questions For the domestic market, does the segmentation based on the party composition and season yield sound estimates of the LMM? Is the improvement of the estimates homogenous across all seasons or party compositions?

4 Data and methodology

4.1 Data: The C.I.T.I. platform

C.I.T.I. was founded in 2003 with the goal of bringing Information Technology services to its members. C.I.T.I. comprises 46 real estate agencies controlling more than 6000 chalets or apartments in 19 different destinations (for futher information about the sources of data see Scaglione et al. (2017)).

The set of data for this research is the same as those used in a previous (Scaglione et al. 2017) study. The data was downloaded on the 20th March 2018 and is restricted to the Swiss resident market. The variables relevant to this study are: season; party composition (number of people); booking date (*bd*), and arrival date (*ad*)—that is the actual travel date and the length of stay. BP was calculated as the difference of "arrival date" and the "booking date" measured in days. The raw data for the domestic market, consists of 92,023 booking transactions. The range for *ad* is from 1st January 2012 to 29 September 2018 and for *bd*, from 12th January 2011 to 18th March 2018.

C.I.T.I has a particular cancelation policy: cancelation without fees can be achieved by notification more than 89 days before the *ad*. If cancellation is notified up to 29 days before *ad,* 50% payment of the rent is required. If cancellation is made less than 29 days before the *ad* 100% of the rent is due (C.I.T.I 2001). C.I.T.I. defines "last minute bookings" as those bookings in which the booking period is between 7 to 28 days. A cancelation could be made without charge 24 to 48 h before the date. In all cases of "free" cancelations, transaction fees will be levied.

The categorization of seasonal variables is the following: High Winter (HW): December, January and February; Low Winter (LW): November, March and April; High Summer (HS): June, July and August and, finally, Low Summer (LS): May, September and October. The categorization for party composition is as follows: less than 3 pax (couples), from 3 to 7 pax (families) and more than 7 pax (groups). Table 1 shows cross frequency table for these two variables.

Table 1 also shows location and dispersion measures of the number of bookings per arrival date by season and party composition. The last column shows the total

Table 1 Basic statistics of the distribution of bookings per recoded arrival date

Seasons	Party	Number of bookings per date					# Bookings (Total)	# Arr. dates (Total)
		Mean	Median	Range	Max	SD		
	Couples	7.37	3	56	57	10.61	3413	452
HS	Families	20.19	7	234	235	33.71	10,879	517
	Groups	4.15	2	31	32	5	1603	370
	Couples	12.08	3	136	137	21.08	5569	496
HW	Families	72.3	7	1214	1215	176.18	37,895	574
	Groups	18.21	4	214	215	37.57	7090	405
	Couples	5.03	2	36	37	7.02	1888	392
LS	Families	11.29	4	161	162	19.4	5366	483
	Groups	2.65	2	13	14	2.22	780	289
	Couples	6.9	3	97	98	12.08	2928	393
LW	Families	23.27	5	649	650	55.75	11,939	482
	Groups	7.23	3	134	135	13.31	2673	329

number of arrival dates present in the database under consideration. This means the dates for which there is at least one booking as the arrival date. The penultimate column shows the total number of bookings. High winter season has the highest number of bookings per date in both the mean and the median. The maximum number for families (1215) shows a concentration of bookings due to the winter holidays. An inspection of the data base shows dates having more than 1000 bookings per day fall on Saturdays of the second and third week of February in 2016, 2017 and 2018. These dates coincide with the beginning of the school vacation calendar.

4.2 Methodology

4.2.1 Kaplan–Meier estimation and sampling methods

The booking period (BP) denotes a variable t_i, which is the indicator of the time lapse between the booking (*bd*) and the arrival date (*ad*). BP is assumed to be the realization of a random process T, where T is the random variable measuring the arrival time or the booking horizon; the probability that a booking arrives on the *ad* time increases as time goes by. For the *BP* cumulative distribution function, we mean: B(t) = Pr(T > t). In order to calculate this function a non-parametric estimator is used: the Kaplan–Meier (KM) estimator (Gémar, Moniche, & Morales, 2016). Figure 1a shows an example of the KM survival distribution, having the length of the BP on the x-axis and the cumulative estimate share of bookings in hand (already made) on the y-axis. Figure 1b shows an example of LMM. The interpretation is that for this sample, the median duration is 100 days and the LMM is 10 days. Half of the expected bookings have already been received (bookings in hand) 100 days

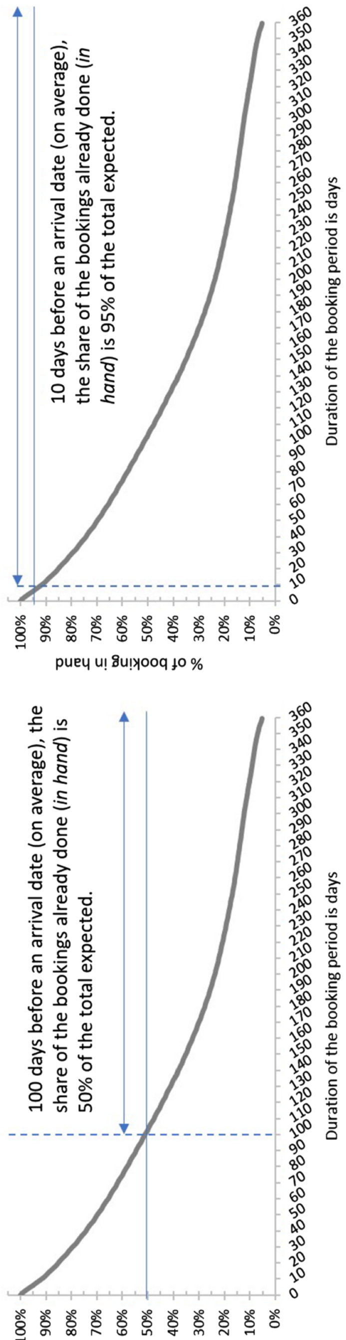

Fig. 1 Example of KM distribution on axis-x BP's duration. BP median = 100 days (left panel) and LMM = 10 days (right panel)

before the arrival day on average. Whereas, 10 days are sufficient to have 95% of the expected bookings (LMM) in hand.

The authors used SAS Institute 9.4 software (*proc surveyselect*) and programmed a customized routine in order to produce and analyse 10,000-simulations: a first routine draws a random sample on the original data set (92,023 booking transactions) having 50 transactions of each combination of the 4 party compositions and 4 seasons, that total $50 \times 4 \times 4 = 800$ transactions. In order to avoid side effects the authors followed the advice of Boehmke, Morey, and Shannon (2006) who suggest that duration estimations based on random simulations help to avoid estimation bias.

A second subroutine performs the estimations of KM that are carried out using the SAS routine *proc lifetest*. These estimates are gathered in SAS SQL database. In the end, for each party/season this process yields 10,000 estimates of LMM, as many as the number of simulations. Once this process is finished the median and the corresponding 95% confidence intervals of LMM is calculated for each of the 16 party compositions/seasons using the bootstrap process using SAS proprietary macro code (SAS Institute Inc. 2007). This median value of the 10,000 simulations is the final LMM estimate for each combination of party/season.

4.2.2 Empirical evaluation of the LMM estimates

In order to empirically evaluate the accuracy of LMM estimates obtained using the process described previously, the authors proceeded in the following way. Firstly, they calculated for each *ad* in the data base, the cumulative booking observed up to the date = *ad* minus LMM estimate, called hereafter, *cut date*. They also calculated the number of overnights as the product of the length of stay and actual number of persons of the party: the number of arrivals is equal to the number of persons. Secondly, measures of accuracy are calculated as the overall geometric average of the percentage of cumulative bookings, overnights, and arrivals after each *cut date* until the *ad*, namely the observed percentage of remaining bookings after the *cut date*. Finally, the inspection of this latter value is expected to be less than 5% and were calculated based on the observed cumulative bookings, overnights and arrivals.

5 Results

Figure 2 shows the histograms of the distributions of the LMM paired in 10,000 simulations per season (panel A) reproduced from Scaglione et al. (2018) and per party composition/season (panel B) yielded by the present research. The histograms in panel (A) have a distribution without *suitable* statistical properties (such as symmetry, the existence of the first and second moments) allowing the calculation of a central value such as the median. They are either not normal (as they are asymmetric or bi-modular) or having a high level of variability in spite of the size of the samples (10,000). The segmentation based on country of origin and season fails to yield a reliable central estimation that also shows that a more precise categorization would be necessary as discussed in Scaglione et al. (2018).

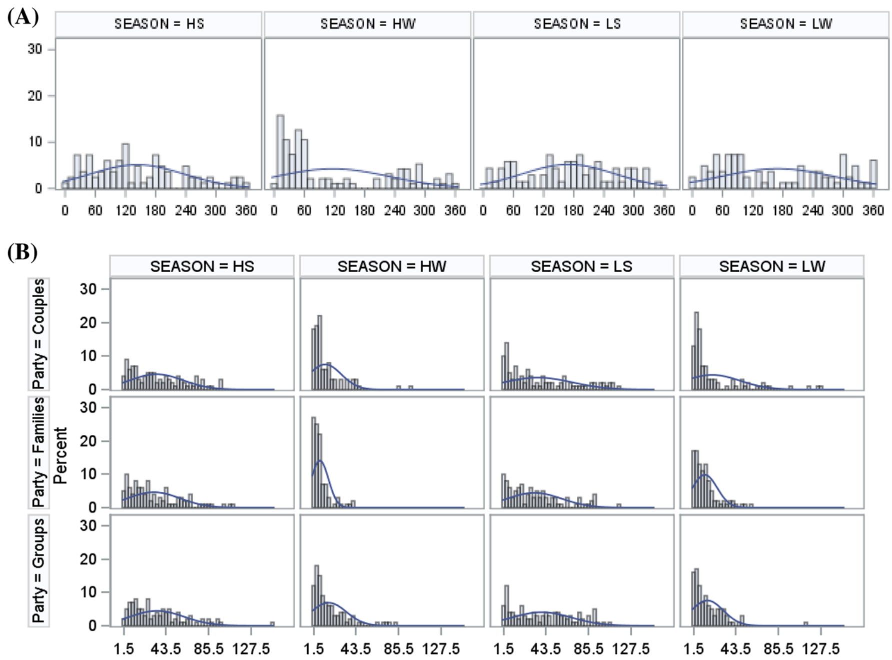

Fig. 2 Histograms of the LMM (in duration of days) paired in 10,000 simulations. **a** Per seasons obtained in (Scaglione et al. 2018). **b** Per season and party (lower row of histograms represents Groups, the middle one Families and the upper one couples or singles) composition. x-axis, number of days (t)

Panel B in Fig. 2, however, shows the distribution shape improvement in terms of lower dispersion when the party composition is considered in the re-sampling process. Table 2 shows the confidence interval (CI) 90% of the LMM estimates obtained in Scaglione et al. (2018) and those obtained after the segmentation by season and party composition. The range of LMM CI's by season/party is less than 2 which is much lower than the ones obtained on the sole basis of season in Scaglione et al. (2018).

As may be seen from Table 2, the empirical measures of accuracy in columns labeled "Observed shares" show, for HW, that the empirical bookings are, on average remaining lower than 10% of the total expected categories for all party categories. For the other seasons, except for LS, LMM for families show slightly good performance.

The estimates of the previous paper Scaglione et al. (2017) yield somewhat better empirical measures of accuracy but the range 90% CI are so large that LMM estimates are not useful in the decision-making process for launching LM sales.

Table 2 Empirical accuracy measures from LMM based on 90% confidence intervals for estimates based on season/party composition and those obtained (Scaglione et al., 2018)

Party	High seasons					Low seasons				
	Season	LMM CI (90%)	Observed share			Season	LMM CI (90%)	Observed share		
			% of LM bookings	% of LM arrivals (guests)	% of ovenigths			% of LM bookings	% of LM arrivals (guests)	% of overnights
Families	*HS*	*[30.6; 31.8]*	*11.91*	*11.91*	14.26	LS	[31.4; 32.5]	15.90	15.71	17.71
Groups	HS	[33.46; 33.49]	19.23	16.54	15.06	LS	[38.5; 39.7]	30.68	24.23	30.41
Couples	HS	[33.4; 34.5]	18.76	18.66	19.69	LS	[34.8; 36.1]	22.15	22.16	19.77
Previous paper	HS	[10; 22]	9.31	8.37	10.28	LS	[9; 33]	10.87	9.63	11.11
Families	*HW*	*[7.5; 7.8]*	***2.22***	***2.16***	***3.87***	*LW*	*[12.4; 12.8]*	***8.21***	***8.01***	***12.47***
Groups	*HW*	*[16.1; 16.7]*	***5.56***	***5.00***	***6.32***	LW	[14.8; 15.4]	11.30	10.26	15.81
Couples	*HW*	*[12.6; 13.2]*	***8.73***	***8.75***	***7.71***	LW	[19.5; 20.5]	16.41	16.28	17.44
Previous paper	HW	[5; 10]	1.39	1.21	2.70	LW	[5,28]	3.78	3.20	7.20

Italic values show best accuracy performance across these categories combination

values in bolditalic observed shares smaller than 10%

6 Conclusions

6.1 Theoretical contribution

This study adds to the literature on last minute buying behaviour, specifically highlighting the importance of season and composition of party. It also adds to the case of the utility of using otherwise unsold inventory as a "win–win" for both sides (Marin-Pantelescu 2016).

This study, in the case of the domestic market, improves LMM estimates by segmentation and by season and composition of the party in comparison to an earlier study Scaglione et al. (2017) that simply considered seasons. Nevertheless, the improvements are not homogenous across the seasons or party composition; only HW and families yield better performance in terms of accuracy. It is noteworthy that both categories have the highest share of the total bookings (see Table 1): HW represents 55% (50,554/92,023) and families 71% (66,079/92,023). Additionally, the slight improvement for HS and LW in the case of family is probably related to the overrepresentation of the family category in the sample.

This raises some questions about the minimum number of observations for the success of the strategy proposed by this research. The combination of seasonal/party that succeed to yield sound LMM estimates have a population of more than 10,000 observations/bookings as Table 1 shows (HS/families = 10,879, HW/families = 37,895, LW/families = 11,939). Even if the data size seems to be "substantial" (more than 90,000 transactions) in comparison to "small data" yielded by survey methods, the question of the size is still relevant. The analysis of Table 1 shows that for all party categories, with the exception of families, the median is less than 5, that means that for date arrivals recorded in the data base, at least, half of them has less than 5 bookings. This suggests that a kind of "critical mass" of the booking per arrival date is necessary to obtain sound LMM estimates.

A previous paper, Scaglione et al. (2017) proposed LMM between 5 and 10 days for HW but these estimates were not very useful for the decision-making process. The span of time in days that make up the decision to launch LM discount was too large. In this research project we not only improved the timing but also we show which segment of the market has to be targeted.

This research project shows for winter that families' LM behaviors materialize one week before the arrival, 10 days for couples and around 2 weeks for groups. This is very interesting and useful information.

6.2 Managerial contribution

This research improves the statistical estimation precision of LMM for all the season/party compositions in spite of the fact that the accuracy is good for some of them as discussed in the previous subsection. The necessity for more grained decomposition could be considered as a methodological complication, nevertheless it is useful from the managerial point of view. The difference across party composition allows real estate vacation rental companies to address different customer segments. Some of these real estate firms are small and medium sized companies (SME's) and probably have limited customer-managed relationship solutions. The segmentation based on the party composition is useful because it allows the company to shape prices and sales oriented by the capacity in terms of numbers of rooms/beds of the object (apartment, cabins, etc.), from the supply side.

In addition, in the case of winter, this information could be used not only for making decisions for LM sales but also for increasing rental prices in the case of high demand for families on the last week before the winter holidays. This research gives a more comprehensive advance forecast of the final frequentation based on the booking in hand in an empirical way for the industry sector, rather than traditional forecasting methods.

7 Limitations and future research

From the point of view of the data quality, some observations have missing values in some relevant variables that had reduced the number of observations under analysis. Furthermore, cancelation transactions are not recorded in the database and this prevents an analysis of the cancelation behavior that could give some interesting insights on RM optimization. This research only tests the limit fixed on the share of 95% of the arrivals as on-hand-booked as the LMM: other share values could be tested in order to test the accuracy in those cases. Recent research that has been undertaken, but not reported in this paper, shows the cluster on weekday arrivals improve the estimations of the LMM.

Future research studies could investigate the differences according to the major international markets for the region, to see if there are any significant differences in last minute behavior based on nationality.

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