Real Estate Fintech: The instant buying business model and its applications in the hotels and resorts industry

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ABSTRACT

Title of the Thesis:

Real Estate Fintech: The instant buying business model and its applications in the hotels and resorts industry

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Keywords: FinTech, PropTech, Instant Buyers, Hospitality

This study aims to analyse the instant buyer business model in the real estate fintech landscape and understand its potential application in the hospitality industry. In order to address this research question, we analysed the ibuyer model in the real estate industry, examining its main success factors and how they might translate to the hotel and resort industry. We also identified the main variables that influence hotel room prices and examined how much they explain hotel selling prices to determine whether automated valuation models (AVMs) can be used to accurately forecast revenues in this industry. In general, the results showed that hotel prices are conditioned not only by observable characteristics of the hotel facility but also by variables that have emerged only recently, such as online reviews on booking portals. Our findings suggest that the ibuyer business model has the potential to be successful in the hospitality industry as well, given that the developed models explain a high share of the variation in reselling prices. Our analysis suggests that AVMs can be a useful tool for hotel room valuation and pricing, although further research is needed to confirm their accuracy and applicability. This research contributes to the existing academic literature on PropTech and the instant buyer business model and has practical implications for managers operating in the hospitality industry, who now have more tools to correctly plan their sales strategy.

ABSTRACT (Portuguese version)

Título:

Real Estate Fintech: O modelo de negócio de compra imediata e as suas aplicações na indústria hoteleira

Autor: Vittorio Gargiulo

Palavras-chave: FinTech, PropTech, Compradores Instantâneos, Hospitalidade

Este estudo tem como objectivo analisar o modelo de negócio do comprador instantâneo no panorama imobiliário fintech e compreender a sua potencial aplicação na indústria hoteleira. A fim de abordar esta questão de investigação, analisámos o modelo ibuyer na indústria imobiliária, examinando os seus principais factores de sucesso e a forma como estes se podem traduzir na indústria hoteleira e de resorts. Identificámos também as principais variáveis que influenciam os preços de quartos de hotel e examinámos o quanto explicam os preços de venda de hotéis para determinar se os modelos de avaliação automatizados podem ser utilizados para prever com precisão as receitas neste sector. Em geral, os resultados mostraram que os preços dos hotéis são condicionados não só pelas características observáveis das instalações hoteleiras, mas também por variáveis que só recentemente surgiram, tais como revisões em linha de portais de reservas. Os nossos resultados sugerem que o modelo empresarial ibuyer tem potencial para ser bem sucedido também na indústria hoteleira, dado que os modelos desenvolvidos explicam uma grande parte da variação dos preços de revenda. A nossa análise sugere que os AVMs podem ser uma ferramenta útil para a avaliação e preços de quartos de hotel, embora seja necessária mais investigação para confirmar a sua exactidão e aplicabilidade. Esta investigação contribui para a literatura académica existente sobre PropTech e o modelo de negócio do comprador instantâneo e tem implicações práticas para os gestores que operam na indústria hoteleira, que agora têm mais ferramentas para planear a estratégia de vendas.

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1. INTRODUCTION

This work is related to the recent papers about technologies that have disrupted the real estate fintech segment and their applications in innovative start-up business models. In particular, the focus is going to be on the proptech innovations applied to the hotels and resorts industry that's one of the biggest worldwide according to GDP. PropTech, or "property and technology," refers to the integration of technology and innovative business models into the real estate industry. This includes high-tech start-ups that use digital, artificial intelligence, and big data in their operations, enabling them to manage large amounts of property information while introducing new products and services to the traditionally slow-moving real estate market (Braesemann & Baum, 2020). PropTech aims to link traditional real estate services with online portals that facilitate the meeting of supply and demand (Baum, 2017). The PropTech industry can be divided into three categories: Smart Real Estate, Sharing Economy, and Real Estate Fintech. In recent years a proptech business model that has been able to disrupt the real estate fintech landscape is the instant buying model. Instant buyers, also known as ibuyers, are companies that use automated valuation models (AVMs) and other technologies to make cash offers on homes quickly through online acquisition platforms (Opendoor). The ibuyer's model significantly reduces the time needed to assess and analyse purchasing decisions and addresses issues faced by home sellers such as the time and effort required to list a home, the delay in accessing cash or purchasing a new home, and uncertainty about the price and time on the market (Buchak et al., 2020). However, ibuyers typically offer lower prices for properties than what a seller might receive if they used a traditional real estate agent and may not enter market segments where it is difficult to algorithmically price properties (Fuster et al. 2019).

This dissertation aims to investigate the feasibility of adapting the instant buyer business model in the hotels and resorts industry. The research question being addressed is: "How can ibuyer's business model be applied to the hotels and resorts industry? What are the main success factors and challenges of this model in the context of hotel room valuation and revenue forecasting?". To answer these questions was crucial to understand if the AVMs, technologies that let the instant buying model disrupt and scale, could also be applied to the hotel and resorts industry. In order to develop this technology, able to instantly compute the monetary value of a hotel room, the first step is to identify the variables that affect room price and occupancy and understand how much they explain hotel room prices. Previous research has shown that there is a strong relationship between room price and customer satisfaction (Mattila & O'Neill, 2003) and that factors such as star rating, hotel age, and distance from the town center can influence

pricing decisions (Israeli, 2002; Bull, 1994). Other attributes that have been found to impact hotel pricing include location, hotel size, and availability of parking spots (Espinet et al., 2003).

There has been no prior research that thoroughly analyses the instant buying model and its critical success factors and limitations in order to assess its potential for disrupting an industry similar to the real estate one, but with its unique dynamics. This research aims to fill this gap by first examining whether the hospitality industry has the necessary characteristics to support the application of the instant buying model and then outlining how a hotel room instant buyer can leverage these advantages to develop a scalable model. In order to achieve this goal, we also describe the financial modelling behind hotel room acquisitions, which illustrates how the business model can operate smoothly and with a reduced risk of default.

The structure of the dissertation is comprised of five main chapters, each of which serves a specific purpose in contributing to the overall research objectives. The second chapter, "Literature Review," presents a comprehensive review of the proptech landscape, the instant buying model in the context of real estate fintech, and the travel and tourism industry. Chapter 3, titled "Data and Methodology," discusses in detail the methods and techniques employed for synthesizing the methodology, collecting, and analysing the data, and defining the sample for the hotel prices dataset. Chapter 4, titled "Results Analysis," presents the empirical results obtained from the analysis of the model, along with a thorough examination of the financial modelling where the results are applied. Finally, Chapter 5, titled "Conclusion," offers a summary of the main findings and suggests avenues for further research based on the results obtained.

1. LITERATURE REVIEW

2.1 PropTech: a disrupting phenomenon

Digital transformation can be defined as the combination of digital technologies and business models (Liu, Chen & Chou, 2011). In recent years consumer expectations have gotten increasingly complex necessitating the redesign of firms' business models, as they now require services that are conveniently accessible at low cost (Mattarocci & Roberti, 2019). For these reasons, the creation of new organizational procedures is something that regards every industry, including real estate (Parviainen, Tihinen, Kääriäinen, & Teppola, 2017). However, the digital revolution's impact on the real estate sector is related to the previous impact it had on the

financial services sector: online payment systems, crowdfunding platforms, property financing, and management serve as the foundation for the development of digital real estate, which is referred to as "PropTech" (Baum, 2017).

PropTech is an abbreviation for "property and technology," and it refers to the application of technology and new business models to the real estate sector. The purpose of this new phenomenon is to connect the services provided by traditional real estate firms with those provided by online portals that allow and facilitate the meeting of supply and demand. However, not all real estate companies that use digital platforms to promote their sales activities are classified as PropTech. PropTechs are high-tech startups that run their businesses on digital, artificial intelligence, and big data. PropTech businesses, which focus on digital technology and innovation, have the potential to manage a significant quantity of property information while also bringing new players and innovative services into the real estate market (Braesemann & Baum, 2020).

2.1.1 Clustering the PropTech industry

The PropTech macro-sector can be distinguished into three different categories identified by Baum (2017): Smart Real Estate, Sharing Economy, and Real Estate Fintech.

“Smart Real Estate” refers to technology platforms that facilitate property operation and management (Baum, 2017). Inside the macro-area of smart real estate, we can find “smart buildings” which represent not only buildings that use advanced technology to improve efficiency, but also entire cities that use high-tech systems to provide efficient services to their residents, such as Singapore, Amsterdam, and Copenhagen (Bellintani, Ciaramella, Celani, Magnani, & Tagliaro, 2018). Smart buildings also provide their owners or users with a more efficient and productive area by integrating new technologies.

The “Sharing Economy” is a disruptive phenomenon that supports, via the use of digital technology, the sharing and exchange of products and services between persons who do not know each other, without the intermediation of third parties (Feth & Gruneberg, 2018). The phenomena began in the late 1990s, thanks to the spread of the internet and web 2.0. These tools supported the creation of online platforms focused on the sharing of content and information, such as publicly accessible information databases. The first thing that comes to mind when we talk about the sharing economy it’s short-term housing rental, a phenomenon

that transformed the tourism sector and the way people travel. Travel sharing is described as a two-party partnership in which one party gives its own house or rooms in exchange for a charge. This phenomenon is becoming increasingly common nowadays. When visiting a new city, renting a full house helps travellers to immerse themselves in the culture and live like a native. Furthermore, rather than renting a room, guests can enjoy larger areas and additional amenities (Valva, 2014). AirBnb has become a global icon of the sharing economy, and it is now the most popular and successful sharing economy platform in terms of growth. Its business model is clear and concise. The host presents a list of available spaces, including single rooms and entire houses, determines the price per night and then gives lodging to quests. Airbnb functions as a true intermediary, connecting supply and demand via a website or mobile application and receiving commissions from both parties (Zervas, Prosperio, & Byers, 2015). Furthermore, most of the available literature has also examined the impact of the "Sharing economy" on the real estate industry. Sheppard and Udell (2018) discover that in New York doubling the number of Airbnb listings leads to a 6% to 11% increase in home values. Barron, Kung, and Proserpio (2021) agree that Airbnb raises home prices, concluding that a tenth increase in Airbnb listings resulted in a 0.026% increase in house prices. Moreover, Horn and Merante (2017) discover that a one standard deviation increase in Airbnb listings is associated with a 0.4% increase in asking rents in the rental market.

Real estate FinTech companies are primarily concerned with the transactional phase of real estate properties, as well as lending, financing, and real estate investment services. Today, this industry is quickly growing and expanding. These platforms provide users with more access to information, providing a high level of transparency. In other words, real estate FinTech seeks to eliminate the informational asymmetry that characterizes traditional markets such as real estate, in which agents select the information to give (Feth & Gruneberg, 2018). The benefit of such services is that they collect a wide range of information and then present a set of inventive, convenient, and easily available alternatives in a relatively short time. In this sector is crucial to differentiate between two types of players: brokers and dealers. Brokerage is the activity of intermediating a real estate acquisition and sale in order to create a great match between those who want to sell a house and those who are looking for one. In general, a brokerage firm invests in the marketing of the property but never participates in the transaction. Nowadays, the use of technology and the development of internet channels are critical for the development of this service since they enable access to real estate investment information (Zumpano, Johnson & Anderson, 2003). The advantage of technical platforms and search engines is that they assist

the buyer's choice by displaying a comprehensive set of adverts from which they can evaluate different market proposals. Within the same industry, a completely different activity is carried on by dealers. Dealers are operators who can shorten market times by entering as part of a real estate transaction. These operators purchase properties at a discount that are later resold on the market at a premium price. As a result, dealers no longer gain from the commission derived from ordinary brokerage activity, but rather from the achievement of a true markup (Benjamin J. Keys et al 2018).

2.2 Instant buyer model in the real estate fintech landscape

Examples of dealers in the real estate market are online fintech lenders such as instant buyers that, thanks to Automated Valuation Models (AVMs) and digital contracting, are now disrupting traditional housing transactions (Buchak et al. 2018; Fuster et al. 2019). Instant buyers, also called ibuyers, use AVMs and other technologies to make cash offers on homes quickly through their online acquisition platforms. An AVM is a computer-based model that uses data and analytics to estimate the value of a real estate property. Opendoor, one of the main ibuyers in the world, also defines instant home buyers as companies that use automated valuation models and other technologies to make cash offers on homes instantly. They have a clear value proposition: sell your home for a guaranteed price, in a short period, and for cash. Applying this vision, they are revolutionizing the real estate market and the way individuals purchase and sell properties by making the transaction simple, fast, and painless. A downside is that ibuyers typically offer lower prices for properties than what a seller might receive if they used a traditional real estate agent to sell their home. This is justified by the better customer experience they offer (Fuster et al. 2019).

These players are addressing different issues for house sellers, which may be clustered into three main groups. The time and effort required to list the home, the delay that may prevent the seller from purchasing a new home or accessing cash, and the uncertainty regarding both the price and time on the market (Buchak et al. 2020). Specifically, home listing entails hassles such as dealing with the standard open houses and home staging, which are a nightmare for working families with several children who need to maintain the house clean for countless showings that span several months. Furthermore, for sellers planning to purchase their next house, the guarantee eliminates the need for costly and stressful second mortgages if the original home does not sell before the new home closes (Seiler et al. 2022). There is extensive literature that studies how search-based frictions affect the housing trading market and how iBuyers may

help alleviate some of these frictions (e.g., Buchak et al. 2020, Wheaton 1990; Genesove and Mayer 1997; Levitt and Syverson 2008; Anenberg and Bayer 2015; Guren 2018; Piazessi, Schneider, and Stroebel 2020). On the other side, some studies show several limitations of ibuyer's business models. These companies tend to rely on hard information for pricing, so they may not enter market segments where it is difficult to algorithmically price properties. Additionally, since homes are empty during the intermediation phase, ibuyers often focus on properties that can be resold quickly (Buchak et al. 2017).

2.2.1 Types of ibuyers business models

In the instant buyers' industry, there are different types of business models and the key differentiator among them is the way they finance acquisitions. The most popular one is the "Buy, Refurb and Resale" developed by the first instant buyers such as Opendoor and Offerpad according to which the ibuyer buys the property and pays out the seller instantly. This model is very capital-intensive because the company must finance the entire home purchase. Another type of ibuyer's model is the "Source/Broker" one where the company only sources residential properties for third-party buyers or institutional investors. For this model, the crucial aspect becomes property management and there is no need to finance the acquisition with own capital or to resell the property. Companies that apply this model are Kodit in Finland and IMMO in Germany. There is also the "Advance" instant buying model that is used only in the UK because it solves a specific problem of their real estate market. In this case, the ibuyer pays the seller only a deposit to allow him to purchase another property before his own is sold. The Advance ibuyer supervises the selling of the house but operates more as a broker than a buyer. In this case, capital is made available for the customer, but it's only required if he needs it before the property is sold.

Our analysis takes into account the first and most widespread model of instant buying the "Buy, Refurb and Resale" which is characterized by the following process: First, a range value of the home is established by the buyer according to automated valuation model estimates. There is no obligation for the seller to accept this offer and usually, it remains valid for a couple of days. Then, if the house meets the ibuyer's criteria an agent performs a free home assessment and a comparative market analysis (CMA) where he identifies recent sales of comparable properties that are as similar as possible to the property being valued. After the inspection, the company makes an actual offer, and the seller can decide if he wants to accept it or take the time to list

his property traditionally. If the seller decides to close, he gets paid in a matter of days (Seiler et al. 2022).

The instant buying business model can be described as a revenue-per-transaction model performed property by property. As a matter of fact, for each transaction, the ibuyers have three primary sources of revenue: the service fee, the home appreciation, and the ancillary services. According to Opendoor, the company charges the home sellers an average service fee of about 6% of home value per transaction which is larger than the typical real estate agent fees. In addition, Buy, Refurb and Resale companies earn thanks to the appreciation which is the difference between the iBuyer acquisition and selling price. On average they achieve more than 5% appreciation of the home value through refurbishment (Ricardo Schäfer, 2018). The last revenue stream is represented by the ancillary services such as title insurance, mortgage, and brokerage services where they earn an average 2.5% commission (Del Prete 2022). Thanks to these revenues, as can we see from figure 1, on average iBuyers can make over ~$30k per sale (assuming an average purchase price of €250k) which is a lot higher than the earnings of traditional or online estate agents. According to Investopedia their commissions generally range between 5% and 6% of the final sale price, though they may be higher or lower based on market conditions.

	% of Transaction Value	US$ Value	Comment
Service fee	7.0%	$17,500	*Fees vary for each property and range from 6-13% depending on state of the home and market*
Appreciation	5.5%	$13,750	*Average based on Opendoor's first year of operation in Phoenix*
Revenue per transaction		**$31,250**	

Note: Assuming average purchase price of $250k

***Figure 1** – Ibuyers' revenue per transaction*

2.2.2 AVMs and price predictability

Several competitive advantages let this model disrupt the real estate market but the most important one is the usage of technology to increase home price predictability which has to be as high as possible for this business model to survive. Ibuyers hold houses to resell so estimating the expected sale price is critically important. Accurately forecasting prices is critical mainly because home value appreciation is one of the major revenue drivers. To enhance price accuracy

instant buyers rely on valuation models, which use historic market data to predict future property prices. According to Opendoor an "Automated valuation model" (AVM) is a proprietary software that ibuyers use to quickly evaluate a large amount of data about a property and arrive at an offer price. AVMs are also defined as “statistic-based computer programs, which use property information to generate property-related values or suggested values” (Matysiak 2017).

The accuracy of AVMs, the different types of machine-learning models, and the comparison between them and the traditional approaches have been object of different research. The discussion has always centered on artificial neural networks (ANNs). Borst (1991) was the first to assess ANNs' ability to produce credible estimations. Do and Grudnitski (1992) are the first to conduct comparison studies of multiple models on the same data set. They tested neural networks on multiple regression in recognizing the price of 136 properties in San Diego. In several following articles, the performance of ANNs outperforms, sometimes significantly, that of classical models (Amri and Tularam, 2012; Kutasi and Badics, 2016).

Traditionally, home values were established by performing a Comparative Market Analysis (CMA), which entails looking at a couple of previously sold similar homes in the area. The issue is that there aren’t two homes that are precisely the same, therefore the agent must adjust for all the different aspects of the selling home. Technology enormously simplifies this process by analysing instantly the individual features of hundreds of comparable houses. As Opendoor explains on its website, their algorithmic pricing reviews comparable homes, accounts for unique features and fine-tunes them based on market trends. One criticism of this model is that it does not consider metadata, particularly negative information that could potentially impact the value of a property. For example, a house that is located in a central location but is situated next to a dangerous neighborhood may not be accurately reflected in the model's valuation.

This process is made possible by machine learning techniques, which absorb data from numerous sources such as Idealista or Immobiliare and make price offers on a property in minutes (Seiler et al. 2022). According to the distribution of Zillow's valuation accuracy data AVMs perform very high average accuracy data. As a matter of fact, if a +/- 10% accuracy figure is regarded as a reasonable margin of error, then approximately 70% of AVM valuations would fall within the +/- 10% range (Matysiak 2017). This level of accuracy can be also improved by applying home valuations techniques such as ensembling. It is a technique used in machine learning and data analysis that involves combining the predictions of multiple

models or algorithms to improve the accuracy of the final prediction. Opendoor describes it as a specific approach that consists in building multiple models for house pricing and then computing a weighted average of their estimates. For example, if one model estimates that a home is worth $95K and another model estimates that it is worth $105K, we might average the two estimates together to make a final estimate of $100K.

Obviously also these techniques present some limitations such as the inability to confirm or deny the existence of a property, the restricted ability to account for external influences, the limited data coverage in some locations (especially rural), and the limited capacity to capture any distinctive property characteristics (Matysiak 2017).

2.2.3 Markets where they choose to operate

There are several studies that suggest that the high levels of accuracy of ibuyers technologies are also a consequence of the markets where they chose to operate. Several findings suggest that ibuyer may choose marketplaces where hard information characteristics explain a higher portion of the variance in transaction pricing and some properties can be precisely valued algorithmically and resold relatively rapidly (Buchak et al. 2022).

Buchak et al. 2022 prove this by asking how much variation in transacted prices can be explained by observable characteristics of the property and local market conditions. They found that observable characteristics explain a substantially higher share of variation in ibuyer transaction prices – both for purchases and sales – relative to transaction prices of other market participants. House characteristics explain roughly 50% of the variation in price for transactions involving ibuyers relative to 40% for transactions by other participants. Michael J. Seiler and Liuming Yang (2022) also support this by showing how ibuyers always enter areas with more easily priced and homogeneous homes by analysing that including zip times quarter fixed effects capturing local market trends, observable house features explain more than 80% of the variation in prices for ibuyer transactions, compared to 68% for non-ibuyer transactions.

2.2.4 Critical success factors and unit economics

Technology and price accuracy aren't the only factors that are playing a crucial role in the spreading of this business model in the real estate industry. Access and cost of capital, the control of variable costs, and operational efficiency are also crucial success factors to survive.

Cost of capital is a key variable because the majority of house acquisitions are financed with debt, as testified by Opendoor's funding, that by 2019 had raised over $3.7 billion, $2.4 of those in debt. For these players is fundamental to find one or more debt partners to finance the house's acquisition process. Based on the data provided by Loric ventures and summed up in figure 2 below, assuming an average cost of capital of 6%, average purchase prices of $250k, and 90% debt financing, iBuyers spend $3.4k on interest each transaction (for a 3-month holding period). Taking an average of 1,000 bought homes per month (12k per year), this corresponds to more than $40 million in yearly interest expenses.

		Holding Period in Months				
		1	2	3	4	5
Cost of capital / APR	10%	1,875	3,750	5,625	7,500	9,375
	8%	1,500	3,000	4,500	6,000	7,500
	6%	1,125	2,250	3,375	4,500	5,625
	4%	750	1,500	2,250	3,000	3,750
	2%	375	750	1,125	1,500	1,875

Note: Assuming 90% of acquisitions financed with debt. Average purchase price $250k

Figure 2 – Interest expenses per transaction (in US$)

The cost of capital, which increases the longer inventory remains on the books, is only one of the variable costs to take under control. Among them, there are also the selling costs that they must pay to agencies in order to resell the house (about 5% of the gross margin), the transaction, and ancillary costs. As a consequence, also operational efficiency is one of the major challenges they have to face. For an ibuyer, each day a home remains on the books negatively affects the overall profitability of the company. Aside from listing and selling speed, operational efficiency is important in many other aspects of the value chain, such as cost-effective client acquisition, customer service, and human resources.

How all these factors play an important role for ibuyers is evident from the unit economics presented in the 2022 ibuyers report by DelPrete. The report shows how ibuyers often present positive contribution margins, which include only direct costs, but negative net margins that considers also indirect expenses. As a matter of fact, the contribution margin is computed by subtracting from the gross margin, the total revenue from a home bought and sold, the selling costs, composed of a buyer's agent commission, the holding costs, and the interest expenses. But this computation doesn't include all expenses still necessary for an ibuyer business such as sales and marketing, salaries, rent, legal, technology, and interest. In 2021 Opendoor despite

having a positive contribution margin of 5.5% closed the year with a net loss of 8.3% (Opendoor's S-4 filing and investor presentation).

	Opendoor	Zillow	Offerpad	
Gross revenue	$8 billion	$6 billion	$2 billion	Includes total value of homes sold
Gross profit	$730 million	($100 million)	$208 million	Fees + home appreciation + ancillary
Gross margin	9.1%	(1.7%)	10%	Fees + home appreciation + ancillary
Contribution margin	5.5%	(6.3%)	6.7%	After selling & holding costs, and interest
Net margin	(8.3%)	(18.7%)	0.3%	After *all* expenses

Figure 3 – Ibuyers' Revenue Comparison 2021

Another drawback is that the ibuyer market share increased during relatively strong times in the property market (2013-2018) when most properties held or appreciated in value. It's uncertain how viable this business model would be in the event of an economic downturn accompanied by a drop in housing values. An increase in the estimated time to resale the property and difficulties appropriately valuing properties in a fast-changing economic climate may also significantly limit, if not completely eliminate, the liquidity provision by iBuyers (Buchak et al. 2020).

2.3 Hotels and resorts industry

The hotels and resorts industry is a segment within the real estate market that has many similarities to the residential property intermediation sector. To better understand this industry and determine whether the instant buying model could be applied to it, it is necessary to examine its key drivers, dynamics, and players.

The hotels and resorts industry is plagued by a structural issue: during the operating season, there is a large number of unoccupied rooms, known as unsold rooms, which results in significant financial losses for hotels. According to Statista the occupancy rate for America's 5.3 million hotel rooms was 66% in 2019, just short of the record high; even so, more than 650 million room nights went unsold (Statista 2022). Moreover, in Italy, the first European market for the number of rooms in 2021, the net occupancy rate of bedrooms in hotels and similar accommodations in 2019 was only 51.8% (Report Gabetti Alberghi Q4 2021). This data underlines the high difficulties that hotel facilities have in reselling high numbers of rooms every day. To avoid this problem and reduce the management risk currently, tourist facilities

try to sell their rooms by exploiting different sales channels such as tour operators (T.O.), traditional travel agencies, and online travel agencies (OTAs) such as Booking.com, which have recently transformed the booking market.

2.3.1 Tour operators

Tour operators (T.O.) are companies that buy in bulk required tourism items such as hotel rooms, airline tickets, transportation, and activities and promote them as a combined all-inclusive package through brochures and other promotional media. (USAID, 2007; Cooper, 2012). They book rooms from hotels based on two types of contracts, which are allotment and commitment contracts:

- A commitment contract is an agreement between tour operators and hotels to block hotel rooms, which upon acceptance of the agreement, rooms will be removed from the hotel's inventory, and the fulfilment of blocked rooms is the tour operator's responsibility, with % 100 non-refundable payments (Devaraja and Deepak, 2014).
- Allotment contract is an agreement between tour operators and hotels where an allocated number of rooms that are pre-agreed between the hotel and the tour operator and 'allotted' to the T.O. and become its responsibility to sell. Moreover, there is a negotiated release back period when if these rooms are not sold, they are released back to the hotel (Industry terminology).

Independent hotels have a low bargaining power compared to these large players and this is the cause of several problems related to room contracting and reselling. First, they have to accept delayed payments both from tour operators and travel agencies. Travel companies are obviously driven to pay as late as possible, whereas hotel establishments prefer to receive payments as early as possible. According to Buhalis et al., this is a major dispute area because it limits an accommodation establishment's ability to meet its own payments to its suppliers (Ivanov et al. 2015).

In their relationship with tour operators, hotels must also accept long negotiation periods, direct competition, and often the release clause. Long negotiation periods are due to the high price sensitivity of these players. Interactions between hotels and tour operators follow a 'zero-sum'/'constant sum' pattern. Due to the tourist's limited budget, one euro extra for one of the parties means one euro less for the other. Both accommodation businesses and travel agencies want to maximize their earnings, and in the short run, attaining this goal means that each side

focuses on getting the most out of every deal/contract. In the long run (from a strategic standpoint), the objectives of both organizations overlap - both want to attract more tourists, which creates more cash for both (Ivanov et al. 2015).

Moreover, hotels suffer also from direct competition because tour operators sell their rooms at lower prices on the same channels and with the hotel brand. Happens that the hotel gives the tour operator the room at a more advantageous price than other distribution actors since the T.O. is able to guarantee a high volume of bookings. The tour operator is supposed to sell these rooms within its tour packages to travel agencies and travellers, but it sometimes happens that, due to the difficulty of selling the whole package, the intermediary prefers to place only the hotel room at the advantageous price offered to him. This means that it is competing directly with the hotel.

Another source of conflict is a condition included in allotment contracts: the release clause. It determines the date until which a travel agency can release back to the hotel the rooms that didn't manage to sell without incurring any costs. Accommodation companies seek longer release periods so that they can sell unused rooms from agency allotments. Shorter release times are preferred by agencies in order to maximize the amount of time available to generate sales. Release periods are being shortened at the expense of lodging establishments due to the increased bargaining power of travel agencies (Ivanov et al. 2015). A common example of a hotel allotment is a contract for 10 rooms with a 14-days release period. This implies you promise the wholesaler that you will hold - i.e., block from any other sales channel - those 10 rooms and that they will only be released to you if the wholesaler has not sold those options up to 14 days before arrival. As a result, hotels are left with a large number of unsold rooms up to 14 days before arrival, causing last-minute price drops on other internet channels to cover part of that vacancy.

2.3.2 Online travel agencies

In the past hotel reservations have been exclusively conducted through tour operators or travel agencies. If a person wanted to make a hotel reservation, he had to use a guidebook and call the hotel directly, but this was expensive and complicated due to international calls, language hurdles, and the potential for fraud. With advancements in information technology, several big travel firms began developing websites that accept direct online reservations (StayNTouch, 2018). At that time, online travel agencies (OTAs) began to emerge. The OTAs are operators

such as Booking, Airbnb, or Agoda which allow consumers to book various travel-related services directly via the Internet. They are marketplaces that collect all the available offers of a specific market.

OTAs main success factors are the increasing visibility provided to hotels that can sell their rooms more easily and the reduced searching costs for travellers when they book a vacation. According to Toh et al. (2011), online travel agencies have significantly contributed to eliminate information asymmetry between consumers and service providers by providing useful and up-to-date information and yet also price transparency. OTAs managed to revolutionize the hotel industry by creating a two-sided market, a market in which one or several platforms enable interactions between two or multiple user groups and charge and govern both of them (Rochet and Tirole 2006). On OTAs, one group is the travellers who are trying to plan their vacations, and the other is the hotel partners who are trying to sell their rooms.

To understand the OTAs business model is crucial to analyse the two main types of pricing that the different players currently use: the agency model and the merchant model. With the agency model, the OTA decides the commission rate while the hotel decides the allocation by controlling the OTA channel price, instead with the merchant model the hotel decides the wholesale price, but the OTA selects the number of rooms to buy (Peng Liao et al. 2016). According to Peng Liao et al., 2016 engaging with an OTA retailer is profitable for the hotel if its capacity is sufficiently high, and the hotel is unwilling to allocate all rooms to the OTA channel. Moreover, they found that the decisions under the merchant model are influenced by the offline price of the rooms and the wholesale price decreases as the hotel's capacity increases. Peng Liao et al., 2016 analysed the agency model, and their research, based on the Stackelberg equilibrium solution, showed that: (1) Working with an OTA retailer is beneficial for the hotel if the available capacity is high enough or the commission rate set by the OTA is low enough. (2) When the hotel's capacity is limited, the optimal commission rate increases; otherwise, it decreases with the hotel's capacity. (3) The OTA prefers the agency model when the hotel's capacity is modest enough; otherwise, the OTA prefers the merchant model.

2.3.4 Hotel rooms instant buyers

Unlike tour operators and OTAs, hotel rooms instant buyers acquire hotel rooms situated in different locations for long time periods, pay a down payment in advance, and re-sell them online at a premium. An ibuyer in the hotels and resorts industry acquires the room management

for the entire hotel opening period (from 5 to 12 months on average), pays an average down payment of 30% in advance and the rest during the season and resells the rooms online with a different brand.

The room acquisition process performed by ibuyers follows three simple steps. First, the hotel fills in an online form with some structural and managerial data such as the number of rooms, distance from the city center, or the number of stars and instantly receives a price range offer computed with a proprietary AVM technology. Then if there is a general price agreement, the ibuyer presents a final offer to the hotel within 24 hours and commits to pay part of the entire amount (about 30%) at a specified date before the hotel opening. From that moment on, room management is entirely their responsibility. A complete analysis of how these firms create and distribute value for their stakeholders is reported through the Canvas Model in Appendix 1.

As in the real estate market, the acquisition process of hotel rooms is entirely based on AVMs that predict the reselling price of hotel rooms and let ibuyers acquire them at the right price in a short timeframe. This AVM forecasts the right everyday hotel selling price by mapping all sale prices and services of hotels located in a specific area and comparing them with the one that needs to be valued. Starting from this point, thanks to machine learning technology, the model can predict the future revenues of that specific hotel room at which is applied a discount to make the monetary offer to the hotel facility.

2.3.5 Hotel forecasting models and price determinants

As in the real estate industry, to develop a technology that can predict future hotel room revenues, it is necessary to understand the main variables that affect room prices and occupancy. Many studies have been conducted to examine the relationship between room rates and their determinants. Mattila and O'Neill (2003) investigated the links between hotel room pricing and customer satisfaction at midscale hotels in the United States and discovered a strong relationship between room price and customer satisfaction. However, little attention has been paid to the elements that hoteliers consider when making fair price decisions. Israeli (2002) investigated if and how star rating and business affiliation influence pricing decisions in different regions. According to the findings, the star rating is a consistent predictor of room prices. Bull (1994) also explored the impact of star rating, hotel age, distance, and transportation considerations on price choice-making. The results show that when the hotel's distance from the town center or hotel age decreases, the room rates increase. Furthermore, Espinet et al.

(2003) investigated the effect of numerous hotel attributes on price and discovered that the town, hotel size, distance to the beach, and availability of parking spots are key predictors of hotel pricing. We add to these findings the impact of other variables such as Booking and TripAdvisor online reviews, the number of restaurants and pools, the room's surface, and the presence or not of a private beach. This analysis is conducted for about 120 Italian hotels with similar characteristics.

Forecast demand accuracy is also crucial to perform this model in the hospitality industry. Evidence of this is demonstrated by Pölt (1998) who shows that a 20% reduction in forecast error leads to a 1% increase in income. Given the importance of accuracy in determining the efficacy of hotel revenue management systems, Schwatz et al. (2016) investigate the possibility of including the competition set aggregated forecast into the predictive model. A two-step recursive procedure is used. First, each competitive set generates its own projection. The projections are then aggregated and combined with a genetic algorithm to generate fresh individual hotel demand predictions. The incorporation of competing set predictions in the hotel occupancy forecasting model improves accuracy, according to both the computer simulation scenario analysis and the empirical field study. Indeed, thanks to this novel approach, the majority of the hotels examined showed a statistically significant improvement. The results show that hotel demand is not only affected by the property's characteristics and policies but also by external factors in the marketplace (Schwarts, Uysal, Webb, & Altin, 2016).

Caicedo-Torres and Payares (2016) confirmed the benefit of integrating a broader range of inputs in the predictive model, observing that models trained on time series plus other variables outperform those trained on time series alone. The major purpose of the paper, however, is to examine the demand forecasting ability of four Machine Learning models. Ridge regression outperforms Kernel Ridge Regression, Multiplayer Perceptron, and Radial Basis Function Networks. Furthermore, the publication is responsive to the needs of the sector. They not only advocate the adoption of Machine Learning models to increase demand forecasting accuracy, but they also emphasize their user-friendliness.

2. DATA AND METHODOLOGY

3.1 Methodology synthesis

The instant buying model has been successful in the real estate industry because it relies on automated valuation methods (AVMs) and other technology-based approaches to accurately

assess and offer fair prices for properties. In order to determine whether this model can be adapted to the hospitality industry, it is essential to identify the key factors that affect hotel room prices and assess how much variation in prices they explain. This is crucial because the ability to accurately value and purchase rooms quickly and efficiently is a key component of the instant buying model. Therefore, in this study, we have conducted a comprehensive analysis of the factors that determine hotel room prices using a panel dataset consisting of daily prices from a sample of Italian hotels. It is through this thorough examination that we can determine whether the instant buying model, with its emphasis on technology and efficiency, can be effectively applied to the hospitality industry.

Panel data or longitudinal data is a set of repeated observations of the same units throughout time. These types of datasets can be used to account for individual heterogeneity and are structured as two-dimensional datasets. The first dimension (t) represents a time series effect, or variation over time, while the second one (i), represents a cross-sectional dimension, or variation across sample units. So, the panel dataset focuses on multiple individuals at multiple time periods. In our analysis, the different individual categories are the hotels while the period goes from May 1st, 2022, until September 30th, 2022. As previous literature suggests when dealing with panel data OLS (Ordinary Least Squares) can be problematic because it does not consider heterogeneity across individuals or years. To avoid this usually fixed effect models or random effect models are implemented.

3.1.1 Fixed effect model

A fixed effect model is a type of ordinary least squares (OLS) model that includes a set of dummy variables for each group in the dataset. This allows the model to control for all time-invariant characteristics of the units being studied, including those that cannot be directly measured or observed. For example, if we are studying the effects of different countries or companies on a particular predictor variable, we can use a fixed effect model to account for the influence of these time-invariant characteristics.

However, it is important to note that the fixed effect model cannot be used to investigate the effects of time-invariant characteristics. For instance, if we want to study the effect of a company's location, this would not be possible using a fixed effect model as the location does not change over time and would be absorbed by the dummy variables in the model. Instead, the

fixed effect model is most appropriate when there is within-individual variation over time, which is not the case in our dataset as the variables we are testing are all time-invariant.

3.1.2 Random effect model

The random effect model is used to estimate the effect of individual-specific characteristics on the response variable in a panel data set. These characteristics, such as age or grit, may be inherently unmeasurable but are thought to affect the dependent variable. This model is appropriate when there are variations between individuals that are expected to affect the outcome of interest. In contrast to the fixed effect model, the random effect model requires fewer parameters to be estimated and can be used even when the individual characteristics being studied are time-invariant. This is because the random effect model assumes that the error terms are not associated with the predictor variables.

There are two main assumptions underlying the use of the random effect model (Greene, 2008):

(1) the observations are drawn from a random sample of a larger population (i.e., the error term u can be considered as a random variable).

(2) the unobserved individual variability is random and unrelated to the model covariates.

3.2 Data collection and sample

The panel dataset for this analysis was compiled using daily prices of hotels located in 20 Italian seaside cities along the Adriatic coast: Rimini, Cattolica, Cervia, Senigallia, Riccione, Ravenna, Milano Marittima, Cesenatico, Igea, MarinaPunta, Marina Lignano, Cavallino, Vasto, Jesolo, Vieste, Caorle, Grado, Lido, Giulianova, and Monopoli. These cities are popular summer vacation destinations and can be grouped into four main touristic areas of interest: the Romagnola Riviera, the Venetian Riviera, the Abruzzo Riviera, and the Ligurian Riviera. The hotels included in the study are all part of the sun-and-beach segment, which is the target market for hotel room buyers. The prices used in the analysis were for a basic room type, with only breakfast included, and were expressed in euros. The research was conducted for a double or twin room type, with the prices averaged on a weekly basis to avoid including daily fluctuations that may be influenced by isolated events in a particular area.

In this study, we collected data that included both traditional observable hotel characteristics, such as the number of stars, room size, and amenities like restaurants and swimming pools, already tested in previous studies (Espinet et al. (2003)), as well as newer variables that have recently gained importance in the hospitality industry, such as the TripAdvisor ranking and customer reviews on Booking.com. By analysing this data, we aimed to provide a more comprehensive understanding of the key drivers of hotel costs and how they influence room price variations.

3.2.1 Web scraping

To collect weekly hotel rates from Booking.com a web scraping software called OTA insights was used. Web scraping is the set of techniques used to automatically get some information from a website instead of manually copying it (Vargiu & Urru 2013). Booking.com has been scraped from May 1st, 2022, until September 30th, 2022, which represents the average opening period of the sun-and-beach hotel segment in Italy. Moreover, our research was filtered for hotels with at least 3 stars and more than 35 rooms that represent the target facilities for ibuyers. The prices extracted for the hotels were the minimum prices for that specific room type.

We chose to scrape hotel rates from the Booking.com website rather than other online travel agencies because Booking is the market leader in Europe and is therefore considered a more reliable source for the Italian hotel industry. Additionally, many hoteliers prefer to use Booking.com for their remaining available rooms because the company's main rival, Expedia, charges higher commissions.

From the database, we removed the data with error values, such as duplicate comments, and then further manipulated some variables to generate dummies. Outlier data were also removed from the study according to the interquartile range methodology since they have a detrimental impact on the model's predictive power. In a dataset, the interquartile range (IQR) is the difference between the 75th percentile (Q3) and the 25th percentile (Q1). It measures the spread of the middle 50% of values. An observation can be defined as an outlier if it is 1.5 times the interquartile range greater than the third quartile (Q3) or 1.5 times the interquartile range less than the first quartile (Q1). The outliers in the dataset were replaced with the mean.

$$Outlier = Observations > Q3 + 1.5*IQR \text{ or } < Q1 - 1.5*IQR$$

3.3 Model analysis

Through an empirical analysis, our model aims to address the following questions: Do the observable characteristics of a hotel facility impact the prices of its rooms? Do these variables help to explain the prices charged by hotels? Are there other factors that also influence room prices? To address these questions, we will estimate the effect of a set of selected variables on hotel room prices and examine how these variables vary across different touristic areas.

Buchak et al. (2018) used a similar approach to study the impact of observable characteristics on transaction prices in the real estate market. Following their example, we have developed a model to understand how much of the variation in hotel room prices can be explained by these observable characteristics. This is an important advantage that ibuyers have over other market participants, as it forms the basis for the technology used to forecast future hotel room revenues.

The empirical method used in this study is a random effect model, as proposed by J.M. Esp inet et al. (2003). This type of model is well-suited for hierarchical data structures, such as our panel dataset which includes pricing data for specific days nested within hotels, which are in turn nested within towns. In addition, random effect models allow us to test the hypothesis that the parameters remain constant across all hotels, locations, and dates. By fitting a single model to the pooled dataset, which includes all hotels and time points, we can increase the efficiency of the analysis.

3.3.1 Dependent and independent variables

In line with previous research on the hotel industry, this study analysed the weekly average of daily hotel room prices as the dependent variable. To avoid issues of endogeneity, the dependent variables were log-transformed. Previous research has shown that endogeneity can emerge as a problem and limit the interpretability of the model (Wei-Ting Hung et al. 2010; J.M. Espinet et al. 2003).

There has been relatively little investigation into the factors that influence hotel pricing decisions. Israeli (2002) and Bull (1994) are among the more recent studies on this topic. Israeli (2002) examined whether and how star rating and company affiliation affect pricing decisions in different locations. The results showed that star rating is a reliable and consistent predictor of accommodation prices and that the number of rooms also plays a role in hotel pricing behavior.

Espinet et al. (2003) and Monty and Skidmore (2003) used the hedonic price approach to examine the determinants of hotel room pricing. This approach allows for the analysis of how the various characteristics of a product, in this case a hotel room, contribute to its price. The studies found that the town, hotel size, distance to the beach, and availability of parking spaces were the most important predictors of hotel room prices. The location has been shown to have a significant impact on hotel prices in numerous studies (Bull, 1994; Israeli, 2002), indeed it is considered to be one of the most important factors influencing hotel room prices.

In this study, we included both explanatory variables that have been previously tested and shown to be significant in previous research, as well as newer variables that have gained increasing importance due to the growing prevalence of online bookings, such as guest rankings and reviews. The final list of variables selected for the study was as follows:

- BADREVIEWS: Percentage of Booking.com reviews with less than 5 stars.
- BOOKING: Booking.com review's average score.
- STARS: The number of hotel stars.
- RMETERS: The hotel room square meters.
- BEACHDIST: The distance from the beach.
- GYM, BALCONY, and BEACH: Dummy coded: 1 for hotels with gym, balcony, or private beach and 0 otherwise.
- POOLS and REST: Number of swimming pools and restaurants for each hotel.
- PARK: The parking cost.
- TRIPADV: The hotel ranking on TripAdvisor based on guests' reviews.
- ROOMS: The total number of hotel rooms.
- CITY: The town where the hotel is located.
- AREA: The tourist area of interest where the city is located.

To estimate the effect of these variables on hotel weekly prices, we employ a random effect model following Espinet et al. (2003) because it allows us to test the hypothesis that the parameters are constant for all hotels, towns, or dates, and also estimate the variance of the parameters across hotels, areas, or dates if the hypothesis is rejected. To increase the accuracy of the model and reduce the risk of overfitting, we initially removed the non-significant explanatory variables such as BADREVIEWS, GYM, and PARK as they did not have a statistically significant effect on the dependent variable. The final model is displayed in Equation (1):

- $Ln\ (\text{PRICE})_{ikj} = \beta_{0ik} + \beta_1(\text{RMETERS})_{ik} + \beta_2(\text{STARS})_{ik} + \beta_3(\text{BEACHDIST})_{ik} + \beta_4(\text{BALCONY})_{ik} + \beta_4\,(\text{POOLS})_{ik} + \beta_5(\text{REST})_{ik} + \beta_6(\text{ROOMS})_{ik} + \beta_7(\text{BOOKING})_{ikj} + \beta_8(\text{TRIPADV})_{ikj} + \mu_{ijk}$ *(1)*

In this model, the *i* subscript represents the hotel (*i* = 1... 125), the *k* subscript indicates the tourist area where its located (k = 1.... 20), and the *j* subscript represents the period (May 1st, 2022, until September 30th, 2022). It is important to note that time-invariant predictors, such as the number of rooms and stars, have only the first two subscripts. The μ_{ijk} is a random error term with zero expectation and constant variance that is independent and identically distributed. In addition, control variables have been included in the model to avoid the potential omitted variable issue. In one of the model specifications, we use area-level control variables to account for unobserved location characteristics.

To test for multicollinearity, we used the variance inflation factor (VIF) approach. In a multivariate regression model, multicollinearity occurs when there is a high correlation between multiple independent variables, which can negatively impact the results of the regression. The VIF measures the extent to which the variance of a regression coefficient is inflated due to multicollinearity. If the VIF values for all variables are less than 2, then there is no multicollinearity present. As shown in figure 4, the summary statistics for the variables indicate that no multicollinearity was found in this study.

```
=========================================
Independent Variable GVIF Df GVIF((1/2*Df)
-----------------------------------------
RMETERS              1.10 1      1.05
STARS                1.70 1      1.30
BEACHDIST            1.11 1      1.05
BALCONY              1.24 1      1.11
POOLS                1.46 1      1.21
REST                 1.20 1      1.09
ROOMS                1.49 1      1.22
BOOKING              1.43 1      1.20
TRIPADV              1.41 1      1.19
factor(AREA)         1.39 3      1.06
-----------------------------------------
```

Figure 4 *- VIF Analysis*

3.3.2 Descriptive statistics

As a first step, we ran a descriptive statistics analysis for the data which highlights the mean, max, min, and standard deviation of the variables used in the study. As we can see from figure

5, the average reviews score on Booking.com is 8.21 out of 10, with the minimum at 6.4 and the maximum at 9,6 (SD=0,64). This shows how the hotels considered in the sample are all upper-scale hotels that represent the ibuyers target market. This is confirmed also by the average number of stars that's 3.45 and ranges from 3 to 5 so there are no 1- or 2-star hotels in the sample. Moreover, the hotel considered present a high number of rooms on average of 47,28 and that's because the facilities with a high number of rooms are the ones that experience the problem of the unsold room that the ibuyers solve. Its standard deviation of 34.68 shows that the sample collected has a good level of variability. On average the hotels in the sample present both a pool (0,76) and a restaurant (0,53). The average price of these facilities is €145 which is perfectly in line with the average ADR (Average Daily Rate) of €150 shown by Gabetti in their Q4 2019 Annual report about the Italian hotel industry.

Statistic	N	Mean	St. Dev.	Min	Max
Bad reviwes	2,125	0.15	1.24	0.00	13.92
Booking score	2,125	8.21	0.64	6.40	9.60
Number of Pools	2,125	0.76	0.84	0	3
Number of Restaurants	2,125	0.53	0.59	0	3
Distance from the beach	2,125	0.84	2.56	0.01	20.00
Stars	2,125	3.45	0.56	3	5
Room square meters	2,125	16.98	4.88	10	35
Number of Rooms	2,125	47.28	34.68	3	282
Price	2,125	145.11	65.56	31.29	480.00

Figure 5 - Descriptive Statistics

4. RESULTS ANALYSIS

4.1 Empirical results

This section analyses and interprets the results of the impact of the main attributes of hotel facilities on their weekly prices. The model proposed in Chapter 3 is implemented. It evaluates the impact of all collected characteristics on lagged prices. Equation (1) is written as follows:

- $Ln\ (\text{PRICE})_{ikj} = \beta_{0ik} + \beta_1(\text{RMETERS})_{ik} + \beta_2(\text{STARS})_{ik} + \beta_3(\text{BEACHDIST})_{ik} + \beta_4(\text{BALCONY})_{ik} + \beta_4\,(\text{POOLS})_{ik} + \beta_5(\text{REST})_{ik} + \beta_6(\text{ROOMS})_{ik} + \beta_7(\text{BOOKING})_{ikj} + \beta_8(\text{TRIPADV})_{ikj} + \mu_{ijk}$ *(1)*

Different model specifications have been used to assess its robustness. The goal is to determine if hotel prices are influenced by the structural characteristics of accommodation facilities and

by elements that have only recently emerged as significant, such as booking reviews and TripAdvisor web ranking. Furthermore, we wish to see if their effect persists when control variables are included in later formulations. In the first specification are included the classical structural characteristics of hotel facilities such as stars, number of rooms, distance from the beach, and number of pools to account for the variables that are considered determinants of hotel prices by previous strands of literature. The goal is to determine whether traditional variables alone explain hotel rates.

	Dependent variable:		
	LN.prezzo		
	(1)	(2)	(3)
Room square meters	0.01***	0.01***	0.01***
	(0.002)	(0.001)	(0.001)
Stars	0.33***	0.27***	0.27***
	(0.02)	(0.02)	(0.01)
Distance from the beach	-0.02***	-0.02***	-0.02***
	(0.003)	(0.003)	(0.003)
Balcony	0.03***	0.02**	0.03***
	(0.01)	(0.01)	(0.01)
Number of Pools	0.04***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)
Number of Restaurants	0.06***	0.09***	0.09***
	(0.01)	(0.01)	(0.01)
Number of Rooms	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0002)
Booking Score		0.20***	0.18***
		(0.01)	(0.01)
Riviera Pugliese			0.08**
			(0.03)
Riviera Romagnola			-0.09***
			(0.02)
Riviera Veneta			-0.20***
			(0.02)
Constant	3.59***	2.15***	2.41***
	(0.07)	(0.11)	(0.11)
Observations	2,125	2,125	2,125
R2	0.31	0.40	0.44
Adjusted R2	0.31	0.40	0.43
F Statistic	939.54***	1,423.09***	1,645.18***
Note:		*p<0.1; **p<0.05; ***p<0.01	

Figure 6 – *Results Analysis*

From the results the coefficients can be interpreted as follows:

- The predicted slope coefficient of stars is 1 = 0.33, implying that a unit increase in the hotel star category results in a 33% change in hotel rates. At the 1% level, the coefficient is statistically significant. This finding supports the hypothesis and is consistent with past research.
- The statistically negative relationship between the distance from the beach and the hotel price is in line with the outcome expected. In general, a 1% increase in distance from the sea translates into a 2% decrease in the price charged.
- An increase in hotel capacity tends to be associated with a price decrease. This is confirmed in figure 6 where the number of rooms is negatively related to the fee charged. Specifically, a unit increase in the number of hotel rooms results in a 0.1% decrease in hotel rates.
- As regards hotel services, the presence of balconies increases prices by 3%. Also, the number of pools and restaurants in the building has a significant effect on price at a 1% significant level. This implies that ceteris paribus, as the number of services offered increases, the hotel can benefit from higher pricing.

It is interesting to note that the star category differs with regard to the extent of its impact on the dependent variable. The magnitude of a change in the hotel start rating dominates the size of a change of the other explanatory variables. These findings are consistent with the findings of the publications described in the literature section, as well as earlier research on the effect of hotel attributes on their prices.

In the first specification are included only structural characteristics while in the second one we add two variables that have gained increasing importance over the years to determine hotel pricing strategies. We collected the hotel's reviews score on Booking.com, the main booking portal in Europe, and their ranking position on TripAdvisor which classifies all the hotels of a specific location according to the fairness of their reviews score. As expected, the two variables are strongly related to each other so to avoid unstable or inconsistent coefficient estimates we removed the TripAdvisor ranking from the regression variables.

The result obtained does not differ a lot from the first model. The star category score is still significant and positively correlated with the average prices, while the other variables maintain more or less the same behavior. It’s crucial to note that the variable added to the model influence

the pricing strategy positively. From figure 6 we can assess as the Booking reviews score becomes the second variable in terms of impact on prices charged. Its predicted slope coefficient is $\beta_7 = 0.20$, implying that a unit increase in review score results in a 20% increase in hotel prices. The coefficient is statistically significant at a 1% significance level.

As the third and last step of the analysis, a third specification is run where the location is included as a control variable and results show that hotels in the "Riviera Romagnola" and "Riviera Veneta" have a negative and significant relationship with room prices, while the opposite is true for hotels in the "Riviera Pugliese." This is likely due to the competitive environment in these tourist areas. Hotel room pricing is heavily influenced by competition, as when there are many hotels in a particular location, they may need to lower their prices to attract customers. This is because consumers have more options to choose from and may be more likely to compare prices and select the most affordable option. According to Sole 24 Ore, the "Riviera Romagnola" has the highest concentration of hotel rooms in Italy, with 3,500 hotels, followed by the "Riviera Veneta." The "Riviera Pugliese" and "Riviera Abbruzzese" areas, on the other hand, have fewer accommodation facilities and are less concentrated.

The relationship between the booking score and the price charged holds constant across all the specifications of the model as the relationship between the star category and the dependent variable. They both persist at the 1% significance level and the magnitude of their coefficient is almost unchanged. In the third model, specifically, the star category remains the most impactful, as a matter of fact, a one-unit increase in a company's star rating results in a 27% increase in prices. The variable booking score presents the same results and it's important to underline that these two variables combined explain the largest part of price changing. Moreover, the results obtained in the second model for the control variables are entirely confirmed.

From this analysis, we can see that in the hotel industry a large share of variation in transacted prices can be explained by observable characteristics of the hotel and its online reviews. As we can see from the R^2 of the model, across specifications, hotel characteristics and online reviews explain roughly 45% of the variation in hotel prices.

4.3 Financial modelling and sensitivity analysis

This empirical analysis has important implications for ibuyers looking to apply the instant buying model to the hotels and resorts industry. The results demonstrate that hotel rooms can be priced with a high level of accuracy using publicly available data about observable characteristics of the hotel facility, similar to how real estate is priced. The regression analysis presented in Chapter 3 serves as the foundation for a pricing algorithm that can quickly forecast future hotel room revenues using machine learning techniques to refine the estimates of the regression coefficients.

These forecasts are crucial for this business model to survive also because they represent the starting point for the financial modelling and sensitivity analysis that ibuyers perform to mitigate their liquidity and default risk. A sensitivity analysis is a method used to assess how the firm's financial performance might be affected by changes in certain variables. The sensitivity analysis conducted by instant buyers is crucial not only to understand the firm cash flows' distribution during the year and its peak exposures but also to evaluate instantly the impact of changes in key variables on the expected company's cash flows. The variables upon which this analysis is based are the hotels' occupancy rate, the terms of payments and the percentage of advanced bookings received.

The occupancy rate is a measure of how much of a hotel's or rental property's capacity is being used. It is calculated by dividing the number of rooms or units that are occupied by the total number of rooms or units available. This data is necessary to compute the effective room revenues by multiplying it with the daily selling price computed by the algorithm with the methodology previously explained. To forecast the occupancy rate, we followed the methodology developed by L.M. Lai and S.C. Wong 2016 that used time series analysis to forecast occupancy rates for serviced apartments.

The terms of payment are also fundamental in this model because the ibuyer doesn't pay in advance all the agreed amount as in the real estate business, but it pays a down payment in advance and then several tranches during the touristic season. This is because it has to protect itself from events that could happen during the hotel opening. As a matter of fact, while the house sale is a one-in-a-time transaction, the hotel rooms must be resold every day for the entire hotel opening period (on average 5 to 12 months). So, the ibuyer has to delay part of the amount in case of an early close of the hotel facility or just to protect itself in case of bad behavior from

the hotel staff with regard to its guests. On average the ibuyer pays a down payment before the opening of 30% of the entire contract. This payment system makes hotel rooms ibuyers a lot less capital intensive than traditional instant buyers because 70% of the contract is financed thanks to the room revenues. So, the actual amount of debt needed is only the one necessary to cover the first advance payment.

The last factor that needs to be estimated to perform a correct sensitivity analysis is the percentage of revenues coming from advanced bookings that the ibuyer manages to cash in before the first payment due date to the hotel. This data is crucial because allows these companies to drastically reduce their debt exposition or completely delete it. It is estimated by taking into consideration the hotel's average booking window which is the length of time between when a hotel guest books a room and when they check in.

Ibuyer's cash flow distribution is affected by these three variables that are a central component of the company's sensitivity analysis. To better understand the process, we analyse the sensitivity analysis for 2023 performed by Hotiday, a hotel rooms instant buyer that operates in the Italian market.

The process starts by developing a financial model for each room acquired based on specific terms of payments, occupancy rate, and the number of advanced bookings received. As an example, consider a room at Hotiday Hotel Garden that was purchased for the upcoming year at 8,500€, using the pricing method previously shown. The room will be available for use from May 9th to September 12th, and the terms of payment for this room are divided into tranches as follows:

Hotiday Hotel Garden	June	July	August	September	Total
Payments	3.400,00 €	1.700,00 €	1.700,00 €	1.700,00 €	**8.500,00 €**

Figure 7 – Payment distribution during the season - Hotiday Hotel Garden

After the payments have been established, the first variable that needs to be estimated in the model is the hotel occupancy rate. This is because the price computed by the algorithm is the average amount of money paid per room per night by the tourists but doesn't take into consideration the number of rooms effectively sold on the available rooms. As mentioned before to forecast the occupancy rate we followed the methodology developed by L.M. Lai and

S.C. Wong 2016 and we predicted an occupancy rate of 75% on average for this hotel during the opening period.

In this model, the last factor that needs to be estimated is the percentage of revenue from advanced bookings that the ibuyer is able to receive from the hotel before the first payment due date. In the example below, we estimated 3000€ of revenues cashed in before the opening period (June 2023) that's based on the hypothesis that the hotel cashs in 20% of the bookings of the next month in advance.

Thanks to these advance sales the debt required to finance this acquisition is equal only to 617€ because the remaining part of the contract is self-financed with the room revenues. The amount of debt needed by instant buyers to finance this model is obtained through credit lines that allow them to borrow money up to a certain limit called the credit limit. They are required to make monthly payments on the credit line, which include interest and a portion of the principal balance but can continue to use the line as long as they make timely payments and do not exceed the credit limit. A complete analysis of debt installments and interest expenses for Hotiday Hotel Garden is reported in Appendix 2.

Cash Flows	April	May	June	July	August	September	October	November	December	Total
Payments			3.400,00 €	1.700,00 €	1.700,00 €	1.700,00 €				8.500,00 €
Room Revenues	171,48 €	489,13 €	2.307,88 €	2.797,71 €	4.986,46 €	893,40 €				11.646,07 €
Cumulated Revenues	171,48 €	660,61 €	2.968,49 €	5.766,21 €	10.752,67 €	11.646,07 €	11.646,07 €	11.646,07 €	11.646,07 €	11.646,07 €
Exposition			-617,04 €	-100,77 €						-717,81 €
Debt Inflow		617,04 €								617,04 €
Debt Repayment			53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	373,13 €
Cumulated Cash Flow	171,48 €	1.277,65 €	132,23 €	1.176,64 €	4.409,79 €	3.549,89 €	3.496,59 €	3.443,28 €	3.389,98 €	3.389,98 €

Figure 8 – Cash Flow Analysis - Hotiday Hotel Garden

Starting from these financial projections developed property by property the ibuyers are able to perform a complete sensitive analysis of their cash flows. These firms pool together all the financial projections developed on each room and control for the variables upon which the model is based. In figure 11, we show Hotiday's sensitivity analysis for the next year that groups the financial models developed for the 50 rooms acquisitions performed by the firm. The cash flow analysis 2023 per single room of the other 8 hotels acquired by Hotiday is reported in Appendix 3.

Cash Flows 2023$	January	February	March	April	May	June	July	August	September	October	November	December	Total
Payments					76.250,00 €	17.000,00 €	59.375,00 €	56.250,00 €	60.444,89 €	28.006,23 €	64.647,73 €	58.512,89 €	**420.486,73 €**
Room Revenues	340,95 €	1.359,18 €	5.983,70 €	18.919,75 €	33.368,47 €	103.051,35 €	98.461,28 €	146.011,64 €	70.279,07 €	54.574,99 €	46.473,36 €	55.323,18 €	**634.146,93 €**
Cumulated Revenues	340,95 €	1.700,13 €	7.683,83 €	26.603,58 €	59.972,05 €	163.023,40 €	261.484,68 €	407.496,32 €	477.775,39 €	532.350,39 €	578.823,75 €	634.146,93 €	**634.146,93 €**
Exposition					-16.277,95 €								**-16.277,95 €**
Equity Inflow													**0,00 €**
Cumulated Cash Flow	**340,95 €**	**1.700,13 €**	**7.683,83 €**	**26.603,58 €**	**-16.277,95 €**	**69.773,40 €**	**108.859,68 €**	**198.621,32 €**	**208.455,50 €**	**235.024,27 €**	**216.849,91 €**	**213.660,20 €**	**213.660,20 €**

Figure 9 – Hotiday's cash flows sensitivity analysis 2023

According to the results displayed in figure 11, the company will only have a peak exposure of €16,000 in May of the next year. The company was able to minimize its capital exposure for payments to hotels by carefully setting the variables that impact the sensitivity analysis. These variables included the stable distribution of payment terms throughout the year, the acquisition of accommodations with different booking windows (that influences the percentage of advance booking received), and the occupancy rates. As a result of this analysis, the company was able to not only reduce the capital required but also minimize the liquidity risk by closely managing its cash flows during the tourist season. This analysis is performed by the company every year and is entirely based on a correct forecasting of future revenues by the pricing algorithm that has at its disposal.

4.4 Unit economics behind hotel rooms ibuyers

To gain a complete understanding of ibuyers' business model dynamics and profitability, it is necessary to examine also their unit economics, similar to how we analysed the ones of players operating in the real estate industry. This is essential because these companies often have high revenues but low profit margins. In the hotel industry, the gross margin is calculated by subtracting the cost of acquiring a hotel room from the revenue generated by reselling it over the entire acquisition period. The gross margin represents the profit made from buying and reselling a hotel room. Specifically, it includes both the fee charged to hoteliers and the ancillary services sold to guests. Then to compute the contribution margin we must subtract all the direct expenses involved in buying and selling hotel rooms such as selling costs, cashback costs, and interest expenses. The selling costs are primarily composed of the commission charged by the OTAs on every sale. On average it's between 15% and 17% (Amenitiz.com) but usually, ibuyers upload on these platforms increased prices so the real commission paid is about 5-7%. The cashback cost refers to the average percentage that the company gives back to its guests as travel credits to increase the retention rate.

To better analyse the hotel rooms ibuyers' UE, we look at the first 30 room acquisitions that Hotiday made on the Italian market. As we can see from figure 8 below, the acquired rooms present an average gross margin of 40% that's computed as the acquisition price minus the selling price forecasted by the algorithm comprehensive of the revenues from the ancillary services. The selling price takes into consideration also a conservative occupancy rate computed by the algorithm of 75% on average. This gross margin is four times higher compared to the one of the ibuyers operating in the residential real estate industry (10% on average according to Opendoor's S-4 filing and investor presentation). This is justified by the higher risk that an ibuyer operating in the hospitality industry carries on and by the very heartfelt pain point resolved by the company for hoteliers.

According to these data, hotel room instant buyers present a positive contribution margin that is on average 20%. This was computed after subtracting from the gross margin 7% of selling costs, 5% of cashback expenses, and 6% of interest expenses (Source: Bis.org). It's important to underline that this unit economics doesn't include all the expenses necessary for a hotel instant buyer to operate. As we can see from the table if we take into consideration also the indirect expenses Hotiday presents a negative net loss (-13%). Indirect expenses are mainly human resources, tech and legal costs, and general and administrative expenses. In total, they represent 32% of the total revenues from room management. This is pretty common for an early-stage start-up, but the goal of the next years is going to be to improve cost efficiency as the company scales and obtain a positive net income within two years. Just to make a comparison, according to Opendoor's S-4 filing and investor presentation, the company in 2021 after 5 years of operations had a positive contribution margin of 5.5% but still a negative net loss of 8.3% where the indirect expenses accounted for 13.8%.

	Hotiday Hotel Palace	Hotiday Hotel Garden	Hotiday Hotel Perla	Hotiday Hotel Center	Hotiday Hotel Europe	Hotiday Hotel Seaside	TOT
Total Revenues	**27.474,60 €**	**11.646,07 €**	**9.621,03 €**	**14.624,42 €**	**8.530,66 €**	**18.993,68 €**	**90.890,45 €**
Occupancy Rate (%)	*65%*	*75%*	*85%*	*80%*	*80%*	*55%*	*73%*
Hotel Payments	16.000,00 €	8.500,00 €	5.500,00 €	7.000,00 €	6.500,00 €	9.000,00 €	56.628,30 €
Gross Margin	**11.474,60 €**	**3.146,07 €**	**4.121,03 €**	**7.624,42 €**	**2.030,66 €**	**9.993,68 €**	**34.262,15 €**
Gross Margin (%)	*42%*	*27%*	*43%*	*52%*	*24%*	*53%*	*38%*
Selling Costs	1.923,22 €	815,22 €	673,47 €	1.023,71 €	597,15 €	1.329,56 €	6.362,33 €
Cashback Costs	1.373,73 €	582,30 €	481,05 €	731,22 €	426,53 €	949,68 €	4.544,52 €
Interest Expenses	976,68 €	976,68 €	976,68 €	976,68 €	976,68 €	976,68 €	5.860,06 €
Contrinution Margin	**7.200,97 €**	**771,86 €**	**1.989,83 €**	**4.892,81 €**	**30,31 €**	**6.737,76 €**	**17.495,24 €**
Contribution Margin (%)	*26%*	*7%*	*21%*	*33%*	*0%*	*35%*	*19%*
Salary Costs	6.014,08 €	2.549,28 €	2.106,01 €	3.201,23 €	1.867,33 €	4.157,64 €	19.895,57 €
Web Platforms	1.209,13 €	512,53 €	423,41 €	643,61 €	375,43 €	835,89 €	4.000,00 €
Offices	521,60 €	221,10 €	182,65 €	277,64 €	161,95 €	360,59 €	1.725,55 €
Other Costs	1.153,04 €	488,76 €	403,77 €	613,75 €	358,01 €	797,12 €	3.814,45 €
EBT	**-1.696,89 €**	**-2.999,80 €**	**-1.126,02 €**	**156,58 €**	**-2.732,41 €**	**586,51 €**	**-11.940,33 €**
ROS							*-13%*

***Figure 10** - UE of the rooms acquired by Hotiday (per single room)*

By analysing the UE of this business model becomes evident that the ability to accurately predict the reselling price is crucial for the survival of a hotel room instant buyer, as it determines the profitability and competitiveness of the company. If the ibuyer is unable to accurately predict the price at which it will be able to resell the rooms, it may end up purchasing rooms at a higher cost than it is able to sell them for, resulting in a loss. On the other hand, if the company can accurately predict the reselling price and set its markup accordingly, it will achieve a higher margin and increase its profitability.

5. CONCLUSIONS AND FURTHER ANALYSIS

In this study, we have conducted a deep analysis of the instant buying model that disrupted the real estate market, intending to understand whether it can be effectively applied to the hotels and resorts industry. To achieve this, we identified the main success factors of the instant buying model and analysed whether they would have a similar impact on the hotels and resorts industry. One of the key success factors that we identified was the use of technology to accurately forecast home selling prices. We, therefore, researched to understand whether this forecasting technology could also be used to predict hotel reselling prices.

Our research findings indicate that, similar to the real estate industry, hotel selling prices are largely explained by a few key determinants, and therefore a forecasting technology could be effectively applied to this industry. To test this, we developed three different models. In the first model, we examined the influence of structural characteristics of the accommodation facility, such as the number of stars, distance from the beach, and number of pools, on hotel prices. These variables had already been shown to have a significant impact on hotel prices in previous studies. In the second model, we also tested determinants that have only recently been identified as significant, such as online reviews on sites such as Booking.com and TripAdvisor. In the final model, we controlled for tourist areas of interest to eliminate variations due to location-specific events. This final specification showed an R^2 of 45%, providing a starting point for the development of a more accurate technology to forecast hotel prices.

Based on these findings, we demonstrate how these results are applied to an ibuyer business model, and why they are crucial to its survival. Specifically, the forecasted revenues of hotel rooms computed using a pricing technology that is rooted in this analysis are used by ibuyers to create financial projections for each room acquisition, which form the basis of their unit economics and profit margins. These projections are then pooled together to perform a complete

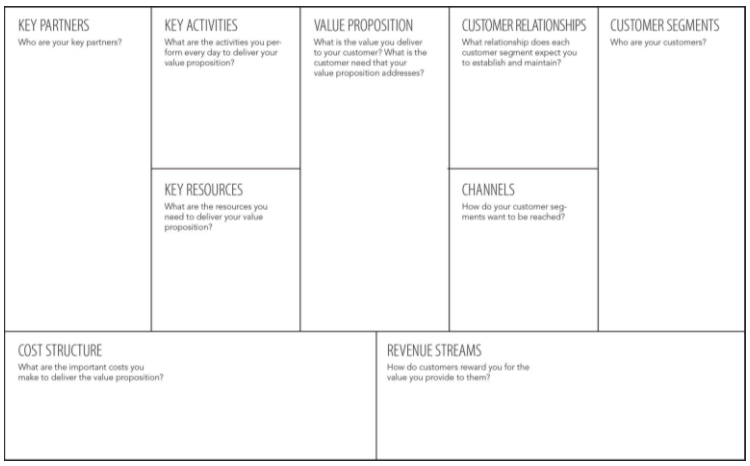
sensitivity analysis of the company's cash flows, which aims to effectively distribute them throughout the year in order to reduce the company's peak exposure and liquidity risk.

This study used a sample of Italian sun and beach hotels and collected prices only for 2022 due to data limitations. In order to further validate these findings, it would be useful to conduct a similar analysis using a larger and more diverse sample of hotels, including business or winter hotels, and consider a broader range of price determinants such as the last year of renovation and parking availability. Additionally, the application of the instant buying model in the hospitality industry is relatively new, so the analysis of unit economics and sensitivity in this study was based on data from a recently founded company. Future research should aim to update these findings by analysing the results of companies operating in this field over time. Moreover, moving forward, further research should explore the potential of machine learning models for revenue forecasting in the hotel industry. This could include examining the impact of different model configurations and parameters on forecasting performance, as well as exploring the potential for combining multiple models for improved accuracy. Machine learning methods such as SVM, random forest, classical regression methods, and a Recurrent Neural Network with Long-short Term Memory, as well as ARIMA and SARIMA models could be tested. Additionally, it would be valuable to investigate the potential for applying machine learning models to other types of data and in other contexts, in order to further understand the capabilities and limitations of these approaches.

APPENDIX

Appendix 1

In order to describe the fundamental characteristics of hotel rooms ibuyers the Canvas Model is presented.



The Business Model Canvas is made up of the following nine parts:

Key resources: one of ibuyers key resources is certainly the high number of destinations that they have in their portfolio and the possibility to add new ones very quickly thanks to a scalable and easily replicable business model. By booking from ibuyers customers can travel with exclusive advantages to many destinations and that's a lot more appealing than the traditional offer of independent hotels where an affiliate program is useless. Another of the companies' main assets is the fact that operate in a market characterized by a high presence of repeating customers.

Key partners: There are several crucial partners to let this business model scale. Firstly, the investors or venture capitalists who opt to fund these new enterprises. They are key players that have to invest in equity in a capital-intensive business during an economic downturn. Fundamental partners are also the ones providing the debt financing. Interest expenses are one of the major cost drivers of this business model so finding a debt partner that can provide financing at good conditions is a key point to survive. Key partners are also the online travel agencies with whom is important to negotiate a good sale commission.

Key activities: The core activities of this business model are contract management with hotels, mortgage approval, and hotel room listing. To scale instant buyers must perform correct room valuations and negotiate with the hotel manager the number of rooms to buy every year, the price to pay, and the payment deadlines. Acquiring the supply at good conditions is the company's key activity. They also have to get mortgage approval from their debt partners to finance the acquisition of new rooms every year. Moreover, all the acquired rooms must be listed on the online travel agencies and on the company's booking platform to be resold.

Value proposition: The value proposition is clear for both the sellers and the buyers.

- Sellers: The company makes the whole process of selling hotel rooms easier with the advantage of getting cash, a quote of guaranteed sold rooms, and a consequent reduction of managing risk. Thanks to their tech-based valuation process, hotels get good prices for their rooms and receive the payment only after a few hours.
- Buyers: For buyers, they get the best-guaranteed price on the market, a travel cashback on every booking that can spend in every destination, and standard services that are always provided to them.

Customer relationship: Ibuyers handle and support new customers through their online booking portal. In order to understand how the company establishes a real trustworthy customer connection is crucial to describe all of the benefits that the company delivers to its visitors when they become members. In fact, becoming a member of the ibuyers travel network can result in significant cost savings, estimated to be over 10%. As a result, their offering results to be far more advantageous and convenient than the one of a standard booking portal.

Customer segment: Two are the main customer segments they address:

- Hotels rooms sellers: This category of customers looks to ibuyers to finance their operations and renewals by selling in advance the hotel rooms that are on average unsold.
- Travelers: These customers aim to book a stay from them because makes the process easier and more convenient. The target customers are specifically digital natives such as young entrepreneurs, freelancers, or employees that are frequent travellers and so can exploit all the advantages of being part of a real digital hotel chain.

Channels: the main channel through which users can choose a location, select the available rooms, or get more information about the hotel is their official website. Through this channel, it is also possible to modify your booking or choose activities or experiences to do in the area. Customers can book also from the OTAs where ibuyers list their rooms. In addition, the company is also actively present on major social networks such as Instagram, Facebook, and LinkedIn.

Cost structure: The main cost drivers in this business model are the following:

- Tech platform management: the maintenance of existing technologies and the development of new ones to improve the company's offer is a major cost driver.
- Marketing: these expenses consist mainly of advertising costs, marketing and branding costs aimed at the continued expansion of the business.
- Cost of capital: this is the cost of funding a business's operations and it's crucial in a capital-intensive type of business such as this one.
- General and administrative: these expenses include staff costs, consultancy costs, and legal expenses.

Revenue stream: The main revenue stream is the fee paid by the hotel owner to reduce its market risk and stabilize its cash flows. This fee is on average 30 to 40% of the offer price but can vary a lot according to the location of the hotel, the quality of the amenities, the demand for rooms in the area, and the terms of the contract. Hotiday is a hotel rooms ibuyer operating in Italy that contractualized 50 rooms in 9 different hotels for the next touristic season. According to their financial plan, their revenues to date may 2024 based on those contracts are 750K considering an 85% occupancy rate of their rooms (conservative approach). The price paid to acquire these rooms was 350k, so this means that the company makes 45% of gross margin on average on each acquisition. Moreover, these companies also present revenues coming from ancillary services including commissions received from third-party service providers such as travel experience platforms or car rental ones. These services are critical in increasing client loyalty and enhancing third-party collaborations.

Appendix 2

Analysis of debt instalments and interest expenses for Hotiday Hotel Garden

Dati Prestito	
Data inizio	giu-23
Ammontare Mutuo	617,04 €
Tasso di int. Annuo	6,7%
Rate	12
Anni Debito	1
Rate Totali	12
Rata mensile	53,30 €
Rata Annuale	639,65 €
Totale Interessi	22,61 €

Interesse	
Data	01/06/2023
Euribor	2,39%
Spread	4,31%

2023	gen-23	feb-23	mar-23	apr-23	mag-23	giu-23	lug-23	ago-23	set-23	ott-23	nov-23	dic-23
Numero Rata						1	2	3	4	5	6	7
Rata		0,00 €	0,00 €	0,00 €	0,00 €	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €
Quota Capitale		0,00 €	0,00 €	0,00 €	0,00 €	49,86 €	50,14 €	50,42 €	50,70 €	50,98 €	51,27 €	51,55 €
Quota Interessi		0,00 €	0,00 €	0,00 €	0,00 €	3,44 €	3,17 €	2,89 €	2,60 €	2,32 €	2,04 €	1,75 €
Debito Residuo	0,00 €	0,00 €	0,00 €	0,00 €	617,04 €	567,18 €	517,04 €	466,62 €	415,92 €	364,94 €	313,67 €	262,12 €

2024	gen	feb	mar	apr	mag	giu	lug	ago	set	ott	nov	dic
Numero Rata	8	9	10	11	12	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Rata	53,30 €	53,30 €	53,30 €	53,30 €	53,30 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Quota Capitale	51,84 €	52,13 €	52,42 €	52,71 €	53,01 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Quota Interessi	1,46 €	1,17 €	0,88 €	0,59 €	0,30 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €
Debito Residuo	210,28 €	158,14 €	105,72 €	53,01 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €	0,00 €

Appendix 3

Hotiday cash flow analysis 2023 per single room.

- Hotiday Hotel Seasise

Cash Flows	February	March	April	May	June	July	August	September	October	November	December	Total
Payments				3.600,00 €		2.700,00 €	2.700,00 €					9.000,00 €
Room Revenues	126,26 €	259,75 €	1.171,78 €	1.729,83 €	4.280,59 €	4.109,35 €	5.952,00 €	1.364,11 €				18.993,68 €
Cumulated Revenues	126,26 €	386,01 €	1.557,79 €	3.287,62 €	7.568,21 €	11.677,56 €	17.629,56 €	18.993,68 €	18.993,68 €	18.993,68 €	18.993,68 €	18.993,68 €
Exposition				-517,86 €								-517,86 €
Debt Inflow				517,86 €								517,86 €
Debt Repayment					44,74 €	44,74 €	44,74 €	44,74 €	44,74 €	44,74 €	44,74 €	313,15 €
Cumulated Cash Flow	126,26 €	386,01 €	1.557,79 €	205,48 €	4.441,33 €	5.805,95 €	9.013,21 €	10.332,59 €	10.287,85 €	10.243,12 €	10.198,38 €	10.198,38 €

Utile
10.198,38 €
54%

- Hotiday Hotel Perla

Cash Flows	March	April	May	June	July	August	September	October	November	December	Total
Payments			2.200,00 €		1.650,00 €	1.650,00 €					5.500,00 €
Room Revenues	63,70 €	211,44 €	697,23 €	2.219,92 €	2.325,91 €	3.871,70 €	231,13 €				9.621,03 €
Cumulated Revenues	63,70 €	275,14 €	972,37 €	3.192,29 €	5.518,20 €	9.389,90 €	9.621,03 €	9.621,03 €	9.621,03 €	9.621,03 €	9.621,03 €
Exposition			-1.288,40 €	-961,09 €							-2.249,49 €
Debt Inflow			1.288,40 €								1.288,40 €
Debt Repayment				111,30 €	111,30 €	111,30 €	111,30 €	111,30 €	111,30 €	111,30 €	779,11 €
Cumulated Cash Flow	63,70 €	275,14 €	60,77 €	2.169,39 €	2.734,00 €	4.844,39 €	4.964,22 €	4.852,92 €	4.741,62 €	4.630,32 €	4.630,32 €

Utile
4.630,32 €
48%

- Hotiday Hotel Europe

Cash Flows	May	June	July	August	September	October	November	December	Dicembre	Total
Payments		1.300,00 €			5.200,00 €					6.500,00 €
Room Revenues	230,10 €	355,34 €	2.088,72 €	1.867,49 €	3.203,46 €	785,55 €				8.530,66 €
Cumulated Revenues	230,10 €	585,44 €	2.674,15 €	4.541,65 €	7.745,11 €	8.530,66 €	8.530,66 €	8.530,66 €	8.530,66 €	8.530,66 €
Exposition		-783,44 €	-475,62 €							-1.259,06 €
Debt Inflow		783,44 €								783,44 €
Debt Repayment			67,68 €	67,68 €	67,68 €	67,68 €	67,68 €	67,68 €	67,68 €	473,75 €
Cumulated Cash Flow	230,10 €	68,87 €	2.089,91 €	3.889,73 €	1.825,52 €	2.543,39 €	2.475,71 €	2.408,03 €	2.340,35 €	2.340,35 €

Utile
2.340,35 €
27%

- Hotiday Hotel Palace

Cash Flows	January	February	March	April	May	June	July	August	September	October	November	December	Total
Payments					6.400,00 €		3.200,00 €		3.200,00 €		3.200,00 €		16.000,00 €
Room Revenues	68,19 €	145,57 €	873,30 €	1.265,99 €	2.668,99 €	5.110,23 €	5.484,18 €	7.646,91 €	2.645,81 €	1.277,78 €	287,65 €		27.474,60 €
Cumulated Revenues	68,19 €	213,76 €	1.087,06 €	2.353,05 €	5.022,04 €	10.132,27 €	15.616,44 €	23.263,36 €	25.909,17 €	27.186,95 €	27.474,60 €	27.474,60 €	27.474,60 €
Exposition					-2.232,79 €								-2.232,79 €
Debt Inflow					2.232,79 €								2.232,79 €
Debt Repayment				192,88 €	192,88 €	192,88 €	192,88 €	192,88 €	192,88 €	192,88 €	192,88 €	192,88 €	1.735,96 €
Cumulated Cash Flow	68,19 €	213,76 €	1.087,06 €	2.160,16 €	469,06 €	5.386,40 €	7.477,70 €	14.931,73 €	14.184,66 €	15.269,55 €	12.164,31 €	11.971,43 €	11.971,43 €

Utile
11.971,43 €
44%

- Hotiday Hotel Center

Cash Flows	April	May	June	July	August	September	October	November	December	Total
Payments		1.750,00 €		2.625,00 €		2.625,00 €				7.000,00 €
Room Revenues	733,17 €	733,17 €	4.602,93 €	3.107,61 €	3.541,80 €	495,00 €	495,00 €	519,75 €	396,00 €	14.624,42 €
Cumulated Revenues	733,17 €	1.466,33 €	6.069,27 €	9.176,88 €	12.718,67 €	13.213,67 €	13.708,67 €	14.228,42 €	14.624,42 €	14.624,42 €
Exposition		-416,97 €								-416,97 €
Debt Inflow		416,97 €								416,97 €
Debt Repayment			36,02 €	36,02 €	36,02 €	36,02 €	36,02 €	36,02 €	36,02 €	252,15 €
Cumulated Cash Flow	733,17 €	133,30 €	4.700,22 €	5.146,81 €	8.652,58 €	6.486,56 €	6.945,54 €	7.429,27 €	7.789,25 €	7.789,25 €

Utile
7.789,25 €
53%

- Hotiday Hotel Vesuvio

Cash Flows	April	May	June	July	August	September	October	November	December	Total
Payments								4.128,30 €		4.128,30 €
Room Revenues						198,86 €	564,57 €	1.481,14 €	2.806,86 €	5.051,43 €
Cumulated Revenues						198,86 €	763,43 €	2.244,57 €	5.051,43 €	5.051,43 €
Exposition								-2.729,44 €		-2.729,44 €
Debt Inflow								2.729,44 €		2.729,44 €
Debt Repayment	235,79 €	235,79 €	235,79 €	235,79 €	235,79 €	235,79 €	235,79 €	235,79 €	235,79 €	2.122,10 €
Cumulated Cash Flow	-235,79 €	-471,58 €	-707,37 €	-943,15 €	-1.178,94 €	-1.215,88 €	-887,09 €	-1.040,60 €	1.530,47 €	1.530,47 €

Utile
1.530,47 €
30%

- Hotiday Hotel Park

Cash Flows	April	May	June	July	August	September	October	November	December	Total
Payments									6.101,33 €	6.101,33 €
Room Revenues							462,86 €	420,00 €	3.531,43 €	4.414,29 €
Cumulated Revenues							462,86 €	882,86 €	4.414,29 €	4.414,29 €
Exposition									-2.549,14 €	-2.549,14 €
Debt Inflow									2.549,14 €	2.549,14 €
Debt Repayment	220,21 €	220,21 €	220,21 €	220,21 €	220,21 €	220,21 €	220,21 €	220,21 €	220,21 €	1.981,92 €
Cumulated Cash Flow	-220,21 €	-440,43 €	-660,64 €	-880,85 €	-1.101,07 €	-1.321,28 €	-1.078,63 €	-878,85 €	-1.119,82 €	-1.119,82 €

Utile
-1.119,82 €
-25%

- Hotiday Hotel Agorà

Cash Flows	January	February	March	April	May	June	July	August	September	October	November	December	Total
Payments									2.281,99 €	1.867,08 €	1.867,08 €	1.867,08 €	7.883,23 €
Room Revenues	772,80 €	1.370,90 €	1.855,55 €	2.098,87 €	2.913,47 €	3.757,30 €	2.498,95 €	2.020,67 €	3.720,97 €	2.704,93 €	2.195,38 €	1.443,45 €	27.353,24 €
Cumulated Revenues	772,80 €	2.143,70 €	3.999,25 €	6.098,13 €	9.011,60 €	12.768,89 €	15.267,84 €	17.288,51 €	21.009,48 €	23.714,41 €	25.909,79 €	27.353,24 €	27.353,24 €
Exposition	175,01 €												0,00 €
Debt Inflow	-175,01 €												-175,01 €
Debt Repayment				-15,12 €	-15,12 €	-15,12 €	-15,12 €	-15,12 €	-15,12 €	-15,12 €	-15,12 €	-15,12 €	-136,07 €
Cumulated Cash Flow	597,79 €	1.968,69 €	3.824,24 €	5.938,23 €	8.866,82 €	12.639,24 €	15.153,30 €	17.189,09 €	18.643,19 €	19.496,16 €	19.839,57 €	19.431,06 €	19.431,06 €

Utile
19.431,06 €
71%

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