EFFECTS OF AIRBNB RENTAL PROLIFERATIONS ON REVPAR OF STAR-RATED HOTELS IN NAIROBI COUNTY

BY

JOY AKOTH AJWANG

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DECLARATION

I declare that this is my original work and that it has not been submitted or presented in any academic institution for the award of any other academic degree or diploma. Except where otherwise noted, this is my original work, and no part of it may be reproduced without the author's and/or Maseno University's prior permission.

Candidate:

Joy Akoth Ajwang (EHM/07209/021)

Signature_____________ Date: ______________

Supervisor:

This project has been submitted for examination under my approval as the candidate's supervisor.

Dr George Otieno Obonyo
Department of Ecotourism, Hotel and Institution Management, Maseno University

Signature_________________ Date: _________________

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To my beloved family, I owe a debt of gratitude that words cannot fully convey. Your unwavering belief in me and your unconditional love have been my anchor during moments of doubt and difficulty. Your constant encouragement and sacrifices have been the driving force behind my aspirations.

Moreover, I am deeply grateful to the divine presence that guides and protects me throughout life's trials and triumphs. To God, I offer my thanks for the strength, resilience, and opportunities bestowed upon me.

DEDICATION

Lastly, I dedicate this project proposal to all the dreamers, believers, and seekers of knowledge. May this humble endeavour contribute, even in the slightest way, to the betterment of our world. Let us continue to explore, learn, and grow, leaving an indelible mark of progress and compassion for generations to come

ABSTRACT

Airbnb is one of the disruptive technologies that have grown exponentially since its inception in 2008. It has raised concerns among hoteliers in the hospitality industry worldwide due to its perceived effect on hotel performance. Nairobi County has seen a surge in the number of Airbnb rentals over the years while at the same time a declining financial performance of star-rated hotels. As a result, there has been a proliferation of studies aimed at understanding the nature of these effects. However, most of these studies have been conducted mainly in the developed economies with reported contrasting results. On the same note, very limited studies have considered Airbnb listings and Airbnb price related factors such as price dispersion and price differentials effects on performance of hotels in Nairobi County, Kenya. This study therefore aimed to investigate the effects of Airbnb proliferations on RevPAR of star-rated hotels in Nairobi County. Specifically, the study set to determine the effect of Airbnb listings on RevPAR of star-rated hotels in Nairobi County; assess the effect of price differentials on RevPAR of star-rated hotels in Nairobi County; identify the effect of Airbnb price dispersion on RevPAR of star-rated hotels in Nairobi, County. The study was anchored on disruptive innovation theory and adopted a quantitative research approach. Correlational research design was used to collect and analyse pooled panel data relating to ADR, occupancy and listings from Airbnb and 54 star-rated hotels in Nairobi County. The study used monthly secondary data for the period between April 2012 to March 2023. Data was subjected to descriptive analysis in Excel and pooled regression analysis in STATA v 13. Descriptive analysis indicates that Airbnb in its initial stage may not be a concern to hoteliers but in the long run does affect the hotel performance. The regression analysis results indicate that Airbnb listings, price differentials and Airbnb price dispersions jointly accounted for 22.4% of the variation in RevPAR of star-rated hotels in Nairobi County ($F [3, 127] = 10.34$, $p < .05$, $R^2 = .224$). The results indicate that a percentage increase in Airbnb listing, price differentials and Airbnb price dispersions would result to a decrease in RevPAR of star-rated hotels in Nairobi County by 0.017%, .13% and .12% respectively. This implies that with Airbnb rentals proliferation in Nairobi County, clients would prefer them to hotels as they charge lower rates and offer convenience. With lower rates, hoteliers would be forced to lower their room rates too and suffer low occupancy rate which in turn affects hotel RevPAR. The findings suggest that hoteliers should closely monitor Airbnb listings and prices and where possible also list some of their rooms on Airbnb. The findings add to the existing body of knowledge by providing insights on the disruptive nature of Airbnb to the hotel industry.

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LIST OF ACRONYMS AND ABBREVIATIONS

Vrbo	**:**	Vacation Rentals by Owner
Airbnb	**:**	Air, Bed and Breakfast
ADR	**:**	Average Daily Rate
RevPAR	**:**	Revenue Per Available Room
Occ	**:**	Occupancy Rate
P2P	**:**	Peer-to-peer
TRA	**:**	Tourism Regulatory Authority

DEFINITION OF TERMS AND CONCEPTS

Active Rentals: Those Airbnb rental facilities that have been active in hosting guests within the study period

Airbnb: Company that operate on a peer-to-peer platform where a host provide accommodation services to the travelling public.

Airbnb Listings: Number of Airbnb supplies listed in Airbnb portal

AirDNA: This is an organisation that provides data and analytics to entrepreneurs, investors, and academic researchers

Average Daily Rate (ADR): Total room revenue collected for a given period divided by the number of rooms sold in that period.

Pooled Panel Data: Data which contain multiple observations or repeated measures of the same variable, taken from the same set of units over time (Hsia, 2014). In this case, the monthly average of hotel ADR, RevPAR, Airbnb ADR and Airbnb listings in Nairobi County overtime.

Price Differential: The gap between a hotel's ADR and the average price of all Airbnb listings in a particular area (Xie and Kwok, 2017)

Price Dispersion: Price variation among all Airbnb listings.

RevPAR: Revenue per available room computed by multiplying ADR and occupancy rate. Can also be computed by dividing the total room revenue for a given period e.g., night by the total number of rooms available in a hotel.

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CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

Technologies have significantly affected how hospitality business operate in today's dynamic business environment (Obonyo, 2016). In particular, digital technologies in the form of disruptive technologies have significantly impacted on the operations of the hotel industry and in turn performance (Ivanov, Seyitoğlu & Markova, 2020; Lenuwat & Boon-itt, 2021; Iranmanesh et al., 2022; Obonyo, 2016). Key among the disruptive technologies in the hospitality industry worldwide is the Airbnb (Hall et al., 2022; Dogru et al., 2020; Adamiak, 2019; Roma, Panniello & Nigro, 2019; Dogru, Mody & Suess, 2018; Lutz & Newlands, 2018; Mody & Gomez, 2018; Mody, Suess & Lehto, 2017).

1.1.1 Airbnb

Airbnb was founded in 2008 and it's an acronym for air, bed and breakfast. It is described as "a trusted community marketplace for people to list, discover, and book unique accommodations around the world - online or from a mobile phone or tablet" (www.airbnb.com). Gutiérrez, Romanillos, García-Palomares & Salas-Olmedo (2017, p. 278) defines Airbnb as "a service that puts travellers in contact with hosts for the purposes of renting accommodation, either rooms or entire homes/apartments". According to Xie and Kwok (2017), it's a platform that connect travellers with local residents who rent out extra accommodation space. It is "…an online platform that gives people around the world (hosts) the opportunity to rent out property as a hospitality service for which they receive a fee" (Janssens, Bogaert &Van den Poel, 2021, p. 1).

To actualise this form of business arrangement, Airbnb operates on the sharing economy principle (Hall et al., 2022; Destefanis, Neirotti, Paolucci and Raguseo, 2020; Gössling and Hall, 2019; Lutz & Newlands, 2018; Gutiérrez et al., 2017; Zervas, Proserpio and Byers, 2017) or what other authors (Guttentag, 2015; Roma et al., 2019; Rolland et al., 2018; Constantinides et al., 2018) refer to as the 'peer-to-peer economy' (Hall et al., 2022; Yang, García, Viglia and Nicolau, 2022; Destefanis et al., 2020; Adamiak, 2019; Benítez-Aurioles, 2019), 'collaborative economy' or 'participative economy' (Gössling and Hall, 2019; Gutiérrez et al., 2017). According to Roma et al. (2019, p. 17), such "…platforms enable people collaboratively share and make use of underutilized resources... (in this context, accommodation facilities) …on a massive scale upon payment".

Alongside Airbnb, other components of sharing economy within the hospitality industry are the Couchsurfing (Kuhzady et al., 2020; Decrop et al., 2018; Chen, 2017) and Vacation Rentals by Owner (Vrbo). While Couchsurfing provides opportunities for guests to be hosted by their host at no cost, Airbnb on the other hand provides a different business model where a guest has to pay for use of Airbnb accommodation facilities making it a more popular peer-to-peer business model in the hospitality industry. Furthermore, Airbnb is considered in this study as it is the largest peer-to-peer platform in the hospitality industry with over 6.6 million active listings in over 220 countries providing accommodation on temporary basis to over 1.4 billion travellers (Airbnb, 2023). Airbnb is now considered a viable option for the public travellers who are seeking alternative accommodation resources to those provided by hotels, hostels, bed and breakfast among other traditional accommodation service providers (Yang et al., 2022; Guttentag, 2015; Kanja, 2018; Zervas, Proserpio, & Byers, 2017; Lutz & Newlands, 2018; Hall et al., 2022). These alternative accommodation resources, according to Kanja (2018), include rental houses, apartments, single rooms, boats or even treehouses.

According to Roma et al. (2019), the hotel sector provides the obligatory features to make such sharing economy channels efficacious, thereby presenting business threats to traditional hotels. They argue that such hospitality resources (beds/rooms/houses) are available in different geographical areas at affordable prices compared to traditional hotel provisions. Similar sentiments are shared by Kanja (2018), who note that travellers are increasingly looking up for cheaper and private accommodation options which are being offered through Airbnb. Additionally, transactions between the provider of the hospitality resource and travellers can be done online due to presence of online digital platforms that support such transactions (Roma et al., 2018; Lutz & Newlands, 2018; Hall et al., 2022; Rolland et al., 2018; Constantinides et al., 2018). Airbnb has to date served over 1.4 billion travellers (Airbnb, 2023) making it one of the key players within the accommodation segment (Hall et al., 2022; Yang et al., 2022; Dogru et al., 2020; Gerdeman, 2018; Zeleski, 2018; Zervas, et al., 2017). Additionally, Airbnb evolution means that it’s now targeting and venturing into the market that was traditional a preserve of the traditional hotels causing more worries in the traditional hotel sector (Zeleski, 2018). This is evidenced by the latest Airbnb offering, Airbnb Plus, which is now targeting business travellers, leisure family market and other upscale travellers (Mody & Gomez, 2018)

1.1.2 Growth of Airbnb

While Gebbia and Chesky founded Airbnb in San Francisco in 2007, according to Airbnb (2023), Gebbia, Blecharczyk and Chesky officially launched it in 2008. Airbnb (2023), indicates that Airbnb operations has increased ever since and as at December 2022, all time earnings by Airbnb host had hit over $ 180 billion spread through over 4million hosts worldwide.

According to Kanja (2018), a 2018 Airbnb report showed that Africa was the fastest-growing Airbnb destination, with more than 3.5 million reservations. The report further indicates that, three of the top eight fastest growing Airbnb destinations are in Africa, with Nigeria leading the way, followed by Ghana, and Mozambique in that order. Kenya, compared to Nigeria at 213%, had 68% increase in bookings through Airbnb listings.

While the concept of Airbnb is traced in San Francisco in 2008, the concept was introduced in Kenya around the year 2012 and has expanded over time. Airbnb listing according to AirDNA (2023), is predominant in the four major cities of Kenya namely Nairobi, Mombasa, Nakuru and Kisumu in that order. According to AirDNA, there was increase in the number of rentals listed in Airbnb from 8,213 in January 2021 to 10,094 in May 2021, accounting for a 23% increase in active listings in Nairobi, Kenya. According to AirDNA (2023) statistics, by the first quarter of 2023, Nairobi had the highest number of Airbnb listings at 12,336 active rentals followed by Mombasa at 3,300 active rentals. This is followed by Nakuru city at 1,723 active rentals and lastly is Kisumu at 915 active rentals. Nairobi also has the highest number of star-rated hotels.

1.1.3 Airbnb and Hotel Performance

At its initiation, it was believed that, Airbnb was not competing the traditional hotels as both were believed to serve different market segments (Mody & Gomez, 2018). However, the success of Airbnb over the years has resulted in a change on this rhetoric, and traditional hotels are now increasingly getting worried over their hotel performance (Hall et al., 2022; Hollander, 2022; Yang et al., 2022; Coles, 2021; Dogru et al., 2020; Prayag et al., 2020; Qiu et al., 2020; Roma *et al*., 2019; Adamiak, 2019; Dogru, Mody & Suess, 2018; Gerdeman, 2018; Müller & Hall, 2018; Mody & Gomez, 2018; Haywood, et al., 2017; Mody, Suess & Lehto, 2017). Gerdeman (2018) in particular noted that the invasion of accommodation sector by Airbnb isn’t being taken lightly and that hospitality associations such as the American Hotel and Lodging Association (AHLA) has indeed launched campaigns to portray Airbnb hosts as commercial entities that compete illegally with hotels. Gerdeman (2018) further notes that Airbnb continues to capture over 12% of travel demand in major travel markets worldwide and, therefore, is considered a number one public enemy by hoteliers all over the world. In spite of this, Hollander (2022) argue that smart hotel owners can actually benefit from Airbnb listing as a distribution channel to increase occupancy and efficiently manage rates.

As a result, academics and industry professionals alike are increasingly interested in studying the effect Airbnb has on conventional hotels performance. In this regard, direct financial performance of hotels attributable to increased Airbnb listings in various hospitality market has drawn wider research attention. Previous research has used financial measures such as revenue per available room (RevPAR), occupancy rates (OCC), and average daily rate (ADR) to understand the effect of Airbnb on performance of hotels in various markets (Dogru et al., 2018, 2019; Dogru, Hanks, Ozdemir, et al., 2020; Dogru, Hanks, Mody, et al., 2020; Haywood et al., 2017; Benítez-Aurioles, 2019; Xie & Kwok, 2017; Dogru et al., 2017b; Zervas et al., 2017). These studies have however been done widely in the US with limited research in other established international markets, including Kenya.

Previous research reported that the increasing supply of Airbnb resulted in a decrease of RevPAR of between 2% and 4% across hotel segments in the US between 2008 and 2017 (Dogru et al., 2018). Similarly, Dogru et al. (2019), investigated the effect of Airbnb listings on performance of hotels in US and concluded that increased availability of Airbnb accommodation had a negative effect on hotel ADR, OCC, and RevPAR. In an attempt to explain this, Roma et al. (2019), suggests that penetration of Airbnb in a given locality causes traditional hotels of a lower grade to adjust their pricing downwards. Similar sentiments are shared by other researchers (for example, Destefanis et al., 2020; Hajibaba and Donlicar, 2017; Zervas et al., 2017; Guttentag, 2015) who argue that not all hotels in a given geographical area would be affected significantly by penetration of Airbnb in the locality. They contend that low and medium end traditional hotels are the most endangered since Airbnb tend to offer low-cost rooms. According to Destefanis et al. (2020), the effect would be reduced if the traditional hotels were located in an attractive geographical area. The implication of their findings is that Airbnb penetration will have significant effect on small and medium end hotel (1–3-star hotels) compared to high quality hotels (such as four and five-star hotels.

The above arguments are also supported by several studies conducted beyond the US markets (e.g., Dogru et al., 2020; Euromonitor International, 2013; Smith Travel Research [STR], 2016a, 2016b; Morgan Stanley Research, 2015; Choi et al., 2015; Neeser et al., 2015; Benítez-Aurioles, 2019). Findings from these studies show that Airbnb supply affected financial performance of hotels. Dogru et al. (2020) for instance investigated the effect of Airbnb listings in Paris, Sydney, London and Tokyo and found that Airbnb availability decreased hotels' RevPAR by between .016% and .031% in the studied markets. On a similar note, Neeser et al. (2015), concluded that Airbnb negatively impacted room prices and RevPAR of hotels in Nordic countries. Similar sentiments were expressed by Bentez-Aurioles (2019), who discovered negative effects of Airbnb on performance of Barcelonian hotels.

On the contrary, a group of researchers believe that Airbnb does present significant threat to hotel performance (Yang & Mao, 2020; Heo et al., 2019; Strømmen-Bakhtiar & Vinogradov, 2019; Blal et al., 2018; Aznar et al. 2017; Borysiewicz, 2017; STR, 2016a, 2016b; Choi et al., 2015; Morgan Stanley Research, 2015; Euromonitor International, 2013) For instance, Euromonitor International (2013) argue that P2P networks such as Airbnb targets different markets from that of traditional hotels and therefore won't affect performance of hotels. Blal et al. (2018), also reported that overall hotel RevPAR would not be affected by Airbnb supply in San Francisco. Similarly, Choi, et al. (2015), did not find significant effect of Airbnb on hotels' revenue in Korea. The implication of this is that penetration of Airbnb does not in any way affect performance of traditional hotels. In support, STR (2016a) argue that tourists only sought Airbnb in situations where there were shortages of traditional accommodation service providers like hotels in US. Further, Morgan Stanley Research (2015) surveyed users of Airbnb in various markets including Germany, US, France, and UK and didn't find any significant change in the market demand for traditional hotels. Similarly, STR (2016b), investigation of Airbnb and performance of hotels in Sydney, Australia, show that in Sydney's accommodation market, fewer than one-third of Airbnb listings were prospective rivals to traditional hotels. The implication of these studies is that Airbnb supply had no discernible impact on hotels' performance in the markets surveyed.

While several studies have investigated the effect of Airbnb on performance of incumbent hotels as evidenced by the foregoing discussions, many of these studies were mainly specific certain geographical markets in the US and some parts of Europe and Asia and therefore lacks generalizability. These markets also present differing contextual setups from the Kenyan market. According Adamiak (2019), Airbnb isn't a uniform segment and a such its effects on hotel performance would vary depending on the territorial context. Despite this, few studies (e.g., Xie and Kwok, 2017) have gone beyond examining the direct effect of Airbnb proliferation on hotel performance and incorporated contextual factors such as price factors and hotel class in understanding the relationship. These investigations have also reported conflicting findings rendering discussions on Airbnb effects on hotel performance inconclusive. The vast majority of the researches are also descriptive in nature and make no inferences about the effect of Airbnb on the hotel sector. There is also lack of study of this nature in the Kenyan Market despite Airbnb listings in Kenya, particularly, Nairobi experiencing exponential growth overtime.

1.2 Statement of the Problem

Airbnb has grown over the years to become one of the key players in the accommodation sector worldwide. While initially Airbnb were thought not to be a threat to operations and performance of traditional hotels as they were perceived to target a different market segment, the continuous incursion of Airbnb has now become a concern for hotel operators worldwide. To date, there over 6.6 million active Airbnb listings in over 220 countries targeting over 1.4 billion travellers all over the world. As such, Airbnb continues to capture over 12% of travel demand in major travel markets worldwide and therefore is considered a number one public enemy by hoteliers all over the world.

One of the concerns elucidated by hotel operators over increasing growth of Airbnb is the ability of Airbnb to incorporate accommodation resources as part of its listings without facing many entry requirements faced by traditional hotels in their entry into the accommodation sector. Per se, Airbnb are perceived to be commercial entities that are operating and competing illegally with traditional hotels due to the fact that it eats into the demand and revenue of traditional hotels. In view of this, various studies have been dedicated to understand Airbnb effect on hotel performance. Previous research has used financial measures such as occupancy rates (OCC), RevPAR and ADR to understand Airbnb effect on performance of hotels in various markets. Findings from these studies are however conflicting and not conclusive with a given set of research indicating Airbnb supply negatively affects hotel performance while another set reporting contrary results. Many of these studies have also focused on hospitality markets mainly in the United States and other international hospitality markets in developed economies in Europe and Asia. While Kenyan accommodation sector has experienced steady growth in Airbnb listings over the years (68%), there is limited study if any that has focused on Airbnb rental proliferation and their effects of on financial performance of star-rated hotels from a developing economy perspective, particularly in Kenya. Furthermore, although price differentials and price dispersions of Airbnb would affect hotel performance, these effects have not been established in the Kenyan market, especially in Nairobi where both Airbnb rental proliferation and star-rated hotels are reported to be high.

1.3 Research Objectives

The primary goal of this research was to look into the effects of Airbnb proliferation on the RevPAR of star-rated hotels in Nairobi County.

1.3.1 Specific Objectives

Specifically, the investigation was guided by three research objectives as listed below:

1. To determine the effect of Airbnb listings on RevPAR of star-rated hotels in Nairobi County
2. To assess the effect of price differentials on RevPAR of star-rated hotels in Nairobi County
3. To identify the effect of Airbnb price dispersion on RevPAR of star-rated hotels in Nairobi County

1.4 Research Hypotheses

The research was guided by three null hypotheses as shown below:

H_{01}: Airbnb listings does not have a significant effect on RevPAR of star-rated hotels in Nairobi County

H_{02}: Airbnb price differentials does not have a significant effect on RevPAR of star-rated hotels in Nairobi County

H_{03}: Airbnb price dispersion does not have a significant effect on RevPAR of star-rated hotels in Nairobi County

1.5 Significance of the Study

There is an exponential increase in the number of rental listings on Airbnb in major tourism destinations worldwide including Nairobi, Kenya. This substantial increase in the quantity of Airbnb rentals penetrating the hospitality and tourism market is significantly transforming operations and performance of various hotels in various markets worldwide. In this regard, various research has been dedicated to understanding Airbnb operations and their impacts on performance of traditional hotels with contradictory findings emerging depending on various market factors. The findings of this current study would, therefore, supplement the existing literature by contributing to the existing debate on Airbnb and hotel performance by analysing the main effects of Airbnb listings, price differentials and price dispersion on RevPAR of star-rated hotels in Nairobi County, Kenya. The findings offer beneficial insights to practitioners of both hotels and hosts of Airbnb rentals in Nairobi and other parts of the country at large by providing informative and insightful facts that would aid in operations of both hotels and Airbnb rental facilities.

1.6 Limitations of the Study

There are a number of platforms that offers accommodation through online platforms including Couchsurfing, Airbnb, online travel agents such as booking.com among others. This study focuses purely on Airbnb, which is a peer-to-peer platform. The study investigates Airbnb proliferation and their effect on RevPAR of hotels (star-rated hotels) in Nairobi County. While financial performance can be measured using many indicators or metrics, this study purely relies on RevPAR as well as ADR to compute price differentials. The study is also limited to hotel segments that are star-rated 2 to 5 stars within Nairobi County, and therefore, the findings should be interpreted with this bearing.

1.7 Assumptions of the Study

The study deals with secondary data for the period between April 2012 to March 2023 collected from different sources including AirDNA, and government documents. There is a total of 12, 336 Airbnb active rentals listed in Nairobi County as at March 2023 (AirDNA, 2023; Airbnb, 2023). The study focused on the monthly ADR for both hotels and Airbnb rental facilities as well as monthly occupancy rates of hotels. Hotel occupancy rates and ADR data for the period was obtained from government records while Airbnb data were obtained from AirDNA and Airbnb.com. The study therefore assumed that secondary data obtained were accurate representation of facts. Where there were variations, the average of the data sources was used instead.

1.8 Conceptual Framework

A conceptual framework depicts the link between the variables under investigation. Figure 1 shows that hotel performance (RevPAR) is affected by Airbnb listings, price differentials, and Airbnb price dispersion.

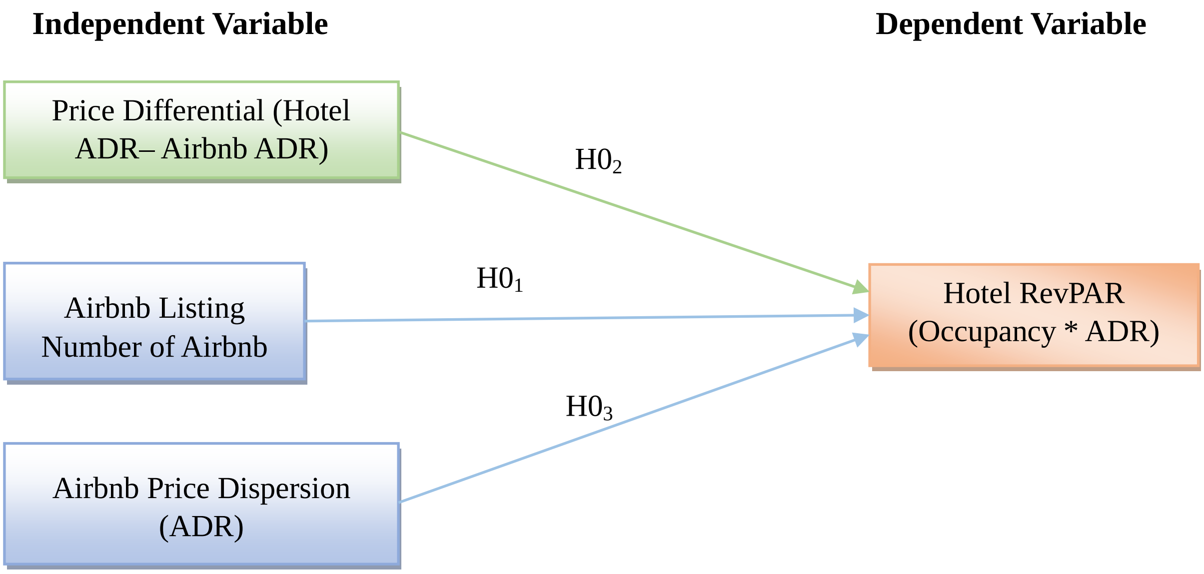

Figure 1.1: **The link between Airbnb proliferation and hotel RevPAR (Adapted and modified from Xie and Kwok, 2017)**

Figure 1 shows that Airbnb listings (supply), price differentials and Airbnb price dispersion would affect RevPAR star-rated hotels in Nairobi County, Kenya. This relationship is anchored on the theory of disruptive innovation, which considers sharing economies or p2p platforms, Airbnb in this case, as a disruptive technology that affect the normal operations of the hospitality industry (Guttentag & Smith, 2017; Dogru et al., 2019; Xie & Kwok, 2017).

CHAPTER TWO
LITERATURE REVIEW

2.1 Airbnb and the Sharing Economy

2.1.1 The Airbnb Concept

The concept of Airbnb, initially referred to as air, bed and breakfast started in 2007 when Joe Gebbia and Brian Chesky hosted three guests in their San Francisco home (Airbnb, 2023). Gebbia, Blecharczyk, and Chesky officially launched it in 2008 and has since increased its operations worldwide accounting for over 4 million hosts and over $180 billion in earnings as at December 2022 (Airbnb, 2023). Various definitions of Airbnb have been put forward in attempt to describe what Airbnb is. Www.airbnb.com define Airbnb as “a trusted community marketplace for people to list, discover, and book unique accommodations around the world - online or from a mobile phone or tablet”. It is also described as “a service that puts travellers in contact with hosts for the purposes of renting accommodation, either rooms or entire homes/apartments” (Gutiérrez et al. (2017, p. 278). Xie and Kwok (2017), describe it as a platform that connect travellers with local residents who rent out extra accommodation space. This study adopts Janssens et al. (2021, p. 1) definition who describe Airbnb is “…an online platform that gives people around the world (hosts) the opportunity to rent out accommodation property as a hospitality service for which they receive a fee”.

Airbnb operates on the sharing economy principle (Hall et al., 2022; Destefanis, Neirotti, Paolucci and Raguseo, 2020; Gössling and Hall, 2019; Lutz & Newlands, 2018; Gutiérrez et al., 2017; Zervas et al., 2017) or what other authors (e.g., Guttentag, 2015; Roma et al., 2019; Rolland et al., 2018; Constantinides et al., 2018) refer to as the ‘peer-to-peer (P2P) networks (Hall et al., 2022; Yang, García, Viglia and Nicolau, 2022; Destefanis et al., 2020; Adamiak, 2019; Benítez-Aurioles, 2019), ‘collaborative economy’ or ‘participative economy’ (Gössling and Hall, 2019; Gutiérrez et al., 2017). Such platform enables hosts and end users to share and make use of underutilized resources (in this context, accommodation facilities) collaboratively upon payment on a large scale (Lutz & Newlands, 2018; Hall et al., 2022; Rolland et al., 2018; Constantinides et al., 2018; Roma et al., 2018). Other hospitality concepts that operate on the sharing economy principle include Couchsurfing (Kuhzady et al., 2020; Decrop et al., 2018; Chen, 2017), which provides opportunities for guests to be hosted by their host at no cost; and Vacation Rentals by Owner (Vrbo). Of the three, Airbnb remains a popular, viable and successful sharing economy platform within the hospitality industry (Hall et al., 2022; Yang et al., 2022; Kanja, 2018; Lutz & Newlands, 2018; Zervas et al., 2017; Xie & Kwok, 2017; Guttentag, 2015). It is therefore the largest P2P platform in the lodging sector (Hall et al., 2022; Yang et al., 2022; Dogru et al., 2020; Gerdeman, 2018; Zeleski, 2018; Zervas et al., 2017) with over 6.6 million active listings in over 220 countries providing accommodation on temporary basis to over 1.4 billion travellers (Airbnb, 2023). These alternative accommodation resources include rental houses, apartments, single rooms, boats or even treehouses AirDNA, 2023; Airbnb, 2023; Kanja, 2018).

2.1.2 Airbnb in Kenya

While the concept of Airbnb is traced in San Francisco in 2008, it remained popular in the US market for the first few years before it expanded to other markets beyond the US (Dogru et al, 2019; Rolland et al, 2018). The concept penetrated the Kenyan market in the year 2012 and has since expanded over time. According to a 2018 Airbnb report, Africa was the fastest-growing Airbnb destination, with more than 3.5 million reservations (Kanja, 2018). The report indicates that, three of the top eight fastest growing destinations for Airbnb are in Africa, with Nigeria leading the way, followed by Ghana, and Mozambique in that order. Kenya, compared to Nigeria at 213%, had 68% increase in bookings through Airbnb listings. Airbnb listing in Kenya, according to AirDNA (2023), is predominant in the four major cities namely Nairobi, Mombasa, Nakuru and Kisumu in that order. Nairobi has since registered an increase in the number of Airbnb listings from 8,213 active rentals in January 2021 to 10,094 in May 2021, accounting for a 23% increase in active listings in Nairobi. According to AirDNA (2023) statistics, by the first quarter of 2023, Nairobi had the highest number of Airbnb listings at 12,336 active rentals followed by Mombasa at 3,300 active rentals. In Nairobi, this represents 93% of the total active rental listings (i.e., 13,264). This represents an exponential quarterly growth of 3% since quarter 1 of 2020 to quarter 1 of 2023. Of the total active Airbnb listings in Nairobi, listings of entire home accounts for 75% followed by listings of private room and shared rooms (AirDNA, 2023). Vrbo on the other hand accounts for 4% with 3% of the total listings representing both Airbnb and Vrbo (AirDNA, 2023). This is followed by Nakuru city at 1,723 active rentals and lastly is Kisumu at 915 active rentals. Nairobi also has the highest number of star-rated hotels.

2.2 Theoretical Review

Many theories can be used to explain the performance of hotels in relation to technological adoption. These include resource-based view (RBV) theory (Barney, 1991), Resource-based theory (RBT) (Penrose, 2009), suppermodularity and complimentarity theory (Milgrom and Roberts, 1990, 1995; Bocquet, Brossard and Sabatier, 2007), disruptive innovation theory

(Christensen, 1995) among others. Given the disruptive nature of Airbnb (Adamiak, 2022; Yang et al. 2022; Hall et al., 2022; Dogru et al., 2020; Bailey, 2017; Guttentag, 2015) this study is anchored on the theory of disruptive innovation.

2.2.1 Disruptive Innovation Theory

Disruptive Innovation Theory (DIT) is traced to the works of Bower and Christensen (1995). The theory, according to Guttentag (2015, p.1192) "describes how products that lack in traditionally favoured attributes but offer alternative benefits can, over time, transform a market and capture mainstream consumers". Dogru et al. (2019), however, argued that despite the popularity of DIT, its fundamental ideas and tenets have been widely misconstrued and misapplied. Despite its criticism by other researchers (e.g., Lepore, 2014; Martin, 2016), DIT has been a subject of essential refinements (Christensen, Raynor and McDonald, 2015) and is now widely applied in recent studies (e.g., Dogru et al., 2019) to understand the disruptive nature of P2P platforms and other sharing economy within the hospitality and tourism industry. Christensen et al. (2015) described disruptive innovations using four tenets such as cheaper, simpler, smaller, and more convenient products in comparison to incumbent products. Other studies including Guttentag and Smith (2017), however, note that a disruptive innovation needs not to be limited only on the four tenets espoused by Christensen et al. (2015), but can take into considerations other benefits including reliability and comfortability among others.

The theory therefore, finds fit in understanding the disruptive nature of Airbnb in the hospitality industry. Disruptive innovation theory, therefore, "…describes how companies may falter not by falling behind the pace of advancement or ignoring their core consumers, but rather by disregarding the upward encroachment of a disruptive product that lacks in traditionally favoured attributes but offers alternative benefits…" (Guttentag, 2015, p. 1194).

2.2.2 Airbnb as a Disruptive Innovation

Various authors (e.g., Adamiak, 2022; Yang et al. 2022; Hall et al., 2022; Dogru et al., 2020; Guttentag, 2015) have examined Airbnb as a disruptive technology in the hospitality industry. There is, however, contention from a given sect of researchers (e.g., Lepore, 2014; Martin, 2016) as to whether Airbnb is indeed a disruptive technology. According to Guttentag (2015), a disruptive technology is meant to disrupt, a therefore, disruptive innovation isn't a change theory as espoused by Lepore (2014), but instead, a competitive response theory (Guttentag, 2015; Dogru et al., 2019). As such, Airbnb is hailed as a game-changing innovation in the hotel industry (Dogru et al., 2019; Bailey, 2017; Guttentag, 2015). In the thoughts of Guttentag (2015), a disruptive product generally underperforms in comparison to the dominant products during its initial entry into the main stream market and appeals only to a specific niche market. Guttentag (2015) goes on to argue that the disruptive product's performance improves over time, making it more appealing to a broader customer base and attracting the attention of the mainstream market.

According to Guttentag (2015), Airbnb is a disruptive innovation as it counters the above arguments against disruption. First, Airbnb was initially unpopular and struggled in the first three years to book rooms of significant amount (Guttentag, 2015). Airbnb also was initially considered to be only appealing to a select group of young tech-savvy and intrepid travelers who were concerned with the room rates (Guttentag, 2015; Rolland et al., 2018). Mody and Gomez (2018), similarly noted that at its initiation, Airbnb was not competing the traditional hotels as both were believed to serve different market segments. However, with time, this notion has changed. More recent studies (e.g., Yang et al., 2022; Zeleski, 2018; Mody & Gomez, 2018; Hajibaba and Dolnicar, 2017; Guttentag and Smith, 2017; Mody et al., 2017; Ting, 2017a; Ting, 2017b) have discredited the notion that Airbnb only appeals to a given niche market. In their study, Mody et al. (2017) discovered that the average Airbnb customer earned more than the average hotel guest and that demand for Airbnb was increasing for both business and leisure-oriented travellers. Guttentag and Smith (2017) on the other hand found that two-third of study participants used Airbnb as a substitute for hotel rooms. Similarly, P2P networks such as Airbnb have been used as hotel substitutes in the Australian hospitality market (Hajibaba & Dolnicar, 2017).

The implication from these studies is that Airbnb is now venturing into the main stream market, a development that is increasingly becoming a concern for traditional hotel owners and operators (Hall et al., 2022; Hollander, 2022; Yang et al., 2022; Coles, 2021; Dogru et al., 2020; Prayag et al., 2020; Qiu et al., 2020; Roma *et al*., 2019; Adamiak, 2019; Dogru et al., 2019; Dogru et al., 2018; Gerdeman, 2018; Müller & Hall, 2018; Mody & Gomez, 2018; Zeleski, 2018; Haywood et al., 2017; Mody et al., 2017). Therefore, the findings of these studies indicate the extent to which Airbnb is a disruptor and the justification to apply the disruptive innovation theory in examining its effects on the incumbent hotels' performance, given an exponential growth of Airbnb rentals.

2.3 Empirical Review

Hotel industry performance has been a subject of discussion among various researchers worldwide. Performance in this case has been measured using both financial and none financial measures. Hotel industry performance has therefore been attributed to a number of factors key among them technological innovations (Obonyo, 2016, Obonyo & Kambona, 2017). Over the years, technological innovation has affected hotel industry performance in terms of its operations, and these technological innovations have been labelled disruptive technologies (Guttentag, 2015; Dogru et al., 2020, Xie and Kwok, 2017; Yang and Mao, 2020) and sustaining technologies (Guttentag, 2015).

2.3.1 Direct effect of Airbnb on Hotel Financial Performance

Previous discussions indicate that Airbnb is one of the major disruptive technologies that is affecting the hotel industry. As a result, various studies (e.g., Yang and Mao, 2020; Dogru et al. 2020; Heo et al., 2019; Strømmen-Bakhtiar and Vinogradov, 2019; Aznar et al., 2017; Borysiewicz, 2017; Dogru et al., 2017b; Xie and Kwok, 2017; Zervas et al., 2017) have investigated Airbnb's impact on the hospitality industry in various contexts.

Several of these studies looked at the direct financial impact of Airbnb supply on the hotel industry. In this regard, financial measures such as OCC, RevPAR and ADR have been used in attempts to comprehend the impact of Airbnb on performance of hotels in US (Dogru et al., 2020; Dogru et al. 2019, 2018; Haywood et al., 2017; Benítez-Aurioles, 2019; Dogru et al., 2017b). According to Dogru et al. (2018), an increase in the supply of Airbnb resulted in a 2% to 4% decrease in RevPAR across hotel segments (luxury hotel segment and economy hotel segment) in the US between 2008 and 2017. Similarly, Dogru et al. (2019) discovered that increased availability of Airbnb accommodation had a negative impact on OCC, ADR, and RevPAR of hotels in the US. In their study, Dogru et al. (2017b) found that a 1% increase in Airbnb availability reduced RevPAR by .025% and ADR by .02% of hotels in Boston. Similarly, Zervas et al. (2017) investigated the impact of Airbnb supply on hotel revenue in Texas and discovered that a percentage increase in Airbnb supply reduced hotel revenue by .04%. An investigation by Xie and Kwok (2017) in Austin, Texas further reported that increasing Airbnb supply significantly brought down hotel RevPAR.

These, according to Roma et al. (2019), was a result of traditional hotels adjusting their prices downwards to compete with Airbnb in their locality. They argue that hotels particularly 1–3-star hotels will naturally adjust their prices downwards if they are located in a geographical area where penetration of Airbnb is higher compared to low and medium end hotels in less penetrated geographical areas. Xie and Kwok (2017) further argue Airbnb supply substitutes the demand for hotel rooms in a given market, hence affect hotel room revenues. This imply that penetration of Airbnb in a given geographical area would significantly affect financial performance of small and medium end hotel (1–3-star hotels) compared to luxury hotels (i.e., hotels rated 4 and 5-star). Similar sentiments are shared by other researchers who contend that although penetration of Airbnb would affect performance of hotels, not all traditional hotels will be affected by penetration of Airbnb in a given geographical area (Guttentag, 2015; Destefanis et al.,2020; Hajibaba & Donlicar, 2017; Zervas et al., 2017). Guttentag (2015) and Zervas et al. (2017), more specifically, argue that low and medium end traditional hotels are the most endangered because Airbnb tend to offer low-cost rooms through peer-to-peer networks. According to them, low and medium end hotels charge almost similar prices for their room to that charged by Airbnb and any higher pricing will automatically come down if they have to remain afloat in the competitive environment. This effect will, however, be reduced if the hotels are located in attractive geographical location (Destefanis et al., 2020). These studies have however been done widely in the US with limited research in other established international markets, including Kenya.

Another set of research particularly those conducted beyond the Unites States (e.g., Dogru et al., 2020; Benítez-Aurioles, 2019; STR, 2016a, 2016b; Choi et al., 2015; Morgan Stanley Research, 2015; Neeser et al., 2015; Euromonitor International, 2013) also indicated that Airbnb supply affect hotels' financial performance. Dogru et al. (2020) for instance investigated the effect of Airbnb listings in four of the world's most important hotel markets namely Sydney, Paris, Tokyo and London. Their study concluded that Airbnb supply in the studied hospitality market negatively affected hotel RevPAR. According to their research, a percentage increase in Airbnb listings would result in a.016 percent to .031 percent decrease in hotel RevPAR in the studied destinations. Similarly, Neeser et al. (2015) examined the impact of Airbnb on hotel prices in Nordic countries. Their findings show that Airbnb negatively affects hotel room prices in Norway, Denmark, Iceland, Finland and Sweden. Similar findings are reported by Benítez-Aurioles (2019), who reported that Airbnb had a negative effect on performance of Barcelonian hotels in Spain. In support, a number of media reports (e.g., Daily Mail, 2016; Gold Coast Bulletin, 2016; Big Hospitality, 2016) suggests that p2p networks such as Airbnb adversely affects proceeds of traditional accommodation service providers. For instance, Gold Coast Bulletin (2016) indicated that p2p platforms reduced demand for rooms in commercial accommodation facilities by over 90,000 room per year.

On the contrary, a group of researchers (e.g., Yang and Mao, 2020; Strømmen-Bakhtiar and Vinogradov, 2019; Borysiewicz, 2017; Heo et al., 2019; Aznar et al. 2017; Blal et al., 2018; Euromonitor International, 2013; STR, 2016a, 2016b; Choi et al., 2015; Morgan Stanley Research, 2015: Haywood et al., 2017) share a different school of thought. They believe that Airbnb does not in any way present significant threat to accommodation provision from hotels. For instance, Euromonitor International (2013) predicted the expansion of traditional lodging facilities to remain the same over the years with no cannibalization effect of p2p platforms such as Couchsurf and Airbnb. This they attribute to the fact that Airbnb target different market segments from that of traditional hotels. Blal et al. (2018), using a mixed model analysis reported that overall hotel RevPAR is not in any way related to total Airbnb supply in San Francisco. Choi et al. (2015) concluded in their study that Airbnb has no significant impact on hotel revenues in Korea. In a similar vein, STR (2016a) concluded in their study that the expansion rate of traditional hotels outclassed Airbnb in six of the seven markets studied in the United States. The implication of this is that penetration of Airbnb does not in any way affect performance of traditional hotels. STR (2016a) argue that tourists only sought Airbnb in situations where there were shortages of traditional accommodation service providers like hotels.

In support of this, STR (2016b) investigation of Airbnb and hotel rooms in Sydney, Australia, reveals that less than one-third of Sydney Airbnb are potential rivals to traditional hotels in the Sydney accommodation market. Morgan Stanley Research (2015) surveyed users Airbnb from the France, US, Germany, and the UK market and found no significant change in the market demand for traditional hotels. This therefore would not translate to any significant impact of performance of the hotels in the markets surveyed. According to Morgan Stanley Research (2015), only 4% travelled because of availability of Airbnb and that the remaining percentage would have used alternative accommodation with 40% citing hotels if Airbnb were not available. Choi et al. (2015) in their study in Korea also stated that Airbnb has no effect on hotel revenues. In fact, they reported that most tourists surveyed in Korea preferred to check into hotels and rather than checking in Airbnb. More recent research (Haywood et al., 2017) note that despite the increasing availability of Airbnb rentals in the US, there was a significant improvement of hotels in terms of occupancy, ADR, and RevPAR. As such, the argue that Airbnb isn’t a threat to conventional hotels per se as argued by other researchers.

While there exist a number of recent studies venturing into understanding of Airbnb and their impact on performance of traditional hotels (Yang et al., 2022; Yang and Mao, 2020; Dogru et al., 2019; Heo et al., 2019; Roma et al., 2019; Strømmen-Bakhtiar and Vinogradov, 2019; Dogru et al., 2018; Lutz & Newlands, 2018; Mody & Gomez, 2018; Rolland et al., 2018; Zeleski, 2018; Aznar et al. 2017; Borysiewicz, 2017; Haywood et al., 2017; Mody et al., 2017; Hajibaba & Donlicar, 2017), majority of the studies have focused on hospitality markets in the United States. Although there exists limited research (e.g., Dogru et al., 2020; Neeser, et al., 2015; Benítez-Aurioles, 2019; Choi, et al., 2015; Adamiak, 2019) examining Airbnb and hotel performance beyond the US hospitality market, these studies have been conducted either in Europe or Asia where the hospitality market operates in the more developed economy. Further, Adamiak (2019) notes that Airbnb isn't a uniform segment and a such its effects on hotel performance would vary depending on the territorial context. The findings of all these studies are also not conclusive in terms of how Airbnb affect performance of commercial hotels, with the findings reported being mixed. Majority of these studies are also descriptive in nature and make no inferences about the impact of Airbnb on the lodging industry. There is also lack of study of this nature in the Kenyan Market despite Airbnb listings in Kenya, particularly, Nairobi, experiencing exponential growth overtime.

2.3.2 Effects of Airbnb Price Factors on Performance of Hotels

While Airbnb effect on hotel performance is acknowledged by a wide body of literature, the nature of this effect tends to vary based on a number of contextual or territorial factors in the hospitality market (Xie and Kwok, 2017; Adamiak (2019). These include price factors such as price differentials (Lee, 2015; Kim, Lee and Roehl, 2016; Xie and Kwok, 2017) and price dispersion (Xie and Kwok, 2017; Kim, Kim and Shin, 2014; Balaguer and Pernías, 2013) as well as contextual elements such as location (Heo et al., 2019), seasonal patterns (Sainaghi and Baggio, 2020), star-rating or grade of hotel (Xie and Kwok, 2017) among others. According to Kim et al. (2016), hospitality establishments that charge higher rates in comparison to their competitors tend to realise better performance in the long run.

All these contextual factors to some extent translate to competitive dynamics which in turn would affect performance of hotels. Previous results of Airbnb effects on performance of hotel have undeniably been challenged for excluding some of these contextual aspects of the hospitality markets. Although Zervas et al. (2017) using a longitudinal study of both 7361 Airbnb supply and 4006 hotels reported that growth of Airbnb listings caused a decrease of hotel earnings in Texas, Heo et al. (2019) criticised these findings for not considering location and seasonal patterns. Financial performance, particularly RevPAR, of a hotel is a function of various factors including prevailing prices in the market, location and grade or rating as well as size of the hotel (Sánchez-Ollero et al., 2014; Lee, 2015). In fact, some authors (e.g., Zervas et al., 2017, Neeser, 2015; Roma et al., 2019; Destefanis et al., 2020; Hajibaba and Donlicar, 2017) argue that penetration of Airbnb in a given geographical region would likely impose a downward pressure on hotels average prices. In the same breath, some authors content that this effect would be negligible, particularly if the hotels within the same region as the Airbnb are of higher rating, implying that prices charged by such Airbnb would not in any way affect performance of such hotels. On the contrary, Blal et al. (2018) argue that higher Airbnb rates would translate to higher ADR for hotels in large cities like San Francisco, hence higher RevPAR if Airbnb were to be considered a substitute product/service. Similarly, Destefanis et al. (2020), contend that the impact of Airbnb on performance of traditional hotels would be reduced if the hotels were located in an attractive geographical area, irrespective of the prices. Blal et al. (2018), however, content that, if Airbnb were to be considered a supplementary service (Hall et al., 2020), then the effect of pricing would be marginal on incumbent hotels. From the forgoing, it's evident that debate on Airbnb proliferation and their effect on incumbent hotels is inconclusive. The debate is further complicated by the need to consider territorial or contextual factors such as location, size of hotel, price factors, grade of hotel/hotel rating, seasonal patterns among others in understanding of this cause-effect relationship. Despite this, few studies (e.g., Xie and Kwok, 2017) have examined the effect Airbnb price factors on performance of hotels.

2.4 Summary of Gaps in Knowledge

The following are the gaps in knowledge identified from literature review that this current study sets to address:

Different studies have examined the effect of Airbnb supply on performance of traditional hotels in different contextual set-ups with variations in their findings. One set of research concludes that Airbnb supply or listings negatively affects financial performance of hotels in terms of occupancy, ADR and RevPAR while another set shows no effect at al.

Majority of the studies have been done in developed economies such as the US, UK, Spain etc., with limited studies in the context of developing economies like Kenya. The findings of extant research may therefore find minimal applications in the Kenyan context given the varying set-ups of these countries. In addition, no study in Kenya has focused on effects of Airbnb and performance of star-rated hotels, particularly in Nairobi County.

Price factors such as Airbnb price dispersions and price differentials have been cited as key considerations in impacting hotel revenues. However, minimal studies have been done focusing on the effect of these price factors on revenues of star-rated hotels in Nairobi County. Extant research has only examined the indirect effects of such factors on the relationship between Airbnb listing and hotel performance through moderation but not on the direct effects.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Study Area

To investigate the effects of Airbnb proliferation on performance of hotels, there is a need to use a unique data set that contains information of both Airbnb and hotels listed in the same market or region (Xie and Kwok, 2017). In this regard, data for this study was collected from star-rated hotel properties and Airbnb rentals in Nairobi County. Nairobi County was considered because it's a major metropolitan area that has experienced exponential growth of vacation rentals (AirDNA, 2023). According to AirDNA (2023), Nairobi is the leading vacation area in terms of Airbnb listing at 12,336 active rentals, followed by Mombasa at 3,300, Nakuru at 1,723 and Kisumu at 915 in that order as at March 2023. Nairobi is also ranked third, among the top cities in Africa with the greatest number Airbnb active rental facilities (Airbnb, 2023; AirDNA, 2023). According to tourism regulatory authority (TRA) (2023), Nairobi County also has the highest number of star-rated hotels compared to other regions in Kenya. Nairobi County has ten five-star hotels, nineteen four-star hotels, fifteen three-star hotels, and nine two-star hotels, totalling to 54 star-rated hotels. Star-rated hotels were considered because they are easily identifiable and are also preferred by travellers when it comes to accommodation provision by hotels. Nairobi, therefore, is the best performing county in relation to both star-rated hotels and Airbnb listing. Results from this study would also serve as a reference to other destinations in Kenya such as Mombasa that are also experiencing high penetration of Airbnb.

3.2 Research Approach and Design

The study used a quantitative approach where quantitative pooled panel data was analysed quantitatively. The study employed a correlational research design as it aimed to look into the effects of Airbnb listings, price dispersion and price differentials on RevPAR of star-rated hotels. The design also allows for the examination of idea development and trends through the use of panel data (Creswell & Creswell, 2018). Furthermore, it was used to describe and quantify the degree or association by utilizing complex relationships among variables found in pooled OLS regression techniques (Creswell & Creswell, 2018; Copper, Heron, and Heward, 2019).

3.3 Study Population

The study targets all Airbnb active rentals listings and star-rated hotels in Nairobi County. There are a total of 12,336 active Airbnb rentals in Nairobi County (AirDNA, 2023) and 54 star-rated hotels in Nairobi County, with the ratings ranging from two star to five star (TRA, 2023). Figure 3.1 shows the distribution of active rentals in Nairobi County with Airbnb listings purely accounting for 93% equalling to 12,336 active Airbnb rentals.

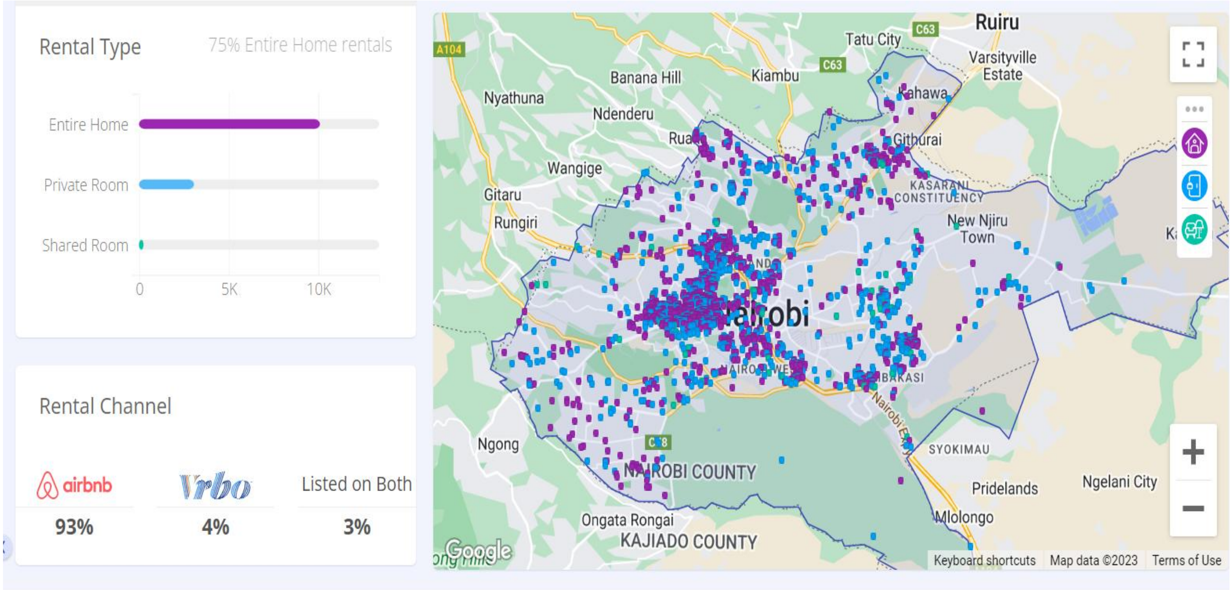

Figure 3.1: Distribution of rental facilities in Nairobi County as at March 2023

Source : https://www.airbnb.com/s/Kenya/homes

A census technique was used in the study, where data from entire targeted facilities (hotels and Airbnb rental facilities) for the study period were considered.

3.4 Data Collection

To address the research objectives, unique pooled panel data set relating to ADR and occupancy rate of hotels and Airbnb rentals in Nairobi County were collected over a period from April 2012 to March 2023 (132 observations) from AirDNA, Airbnb.com, and government annual reports from Central Bank and Kenya National Bureau of Statistics (KNBS). According to Eom, Sock and Hua (2007, p. 572), "…in a data set, the number of repeated measurements on the same variables on the same population or sample can be as small as two. Thus, 132 observations were deemed adequate for this study. The number of Airbnb listings and supplemental information over the said period was obtained from Airbnb.com. Monthly data on average occupancy rate and ADR was obtained from published annual government reports for the said period. This was used to compute average hotel RevPAR for the months within the data collection period. Data on Airbnb ADR and listings was obtained from AirDNA for the said period of data collection. Airbnb listings from Airbnb.com was used to supplement and validate information obtained from AirDNA.

Pooled panel data or just pooled data, also called cross-sectional time series data in other discipline (Eom et al., 2007; Choudhury and Chetty, 2018), was considered in this study as it provides a greater leverage on issues of causal ordering, as was the case in this study, than static cross-sectional data (Hsiao, 2014). The pooled panel data set was unbalanced. The central premise of pooled regression is that the spatial and temporal dimensions do not distinguish between observations and that there is no set of fixed effects in the data (Choudhury & Chetty, 2018).

3.5 Variable Measurement

The main independent variables in this study were Airbnb listings, Airbnb price dispersion and price differentials. Airbnb listings was measured as the total number of active Airbnb rentals facilities including rentals of entire home, shared room, and private rooms at a given time. Rentals of entire home account for 75% of Airbnb listings in Nairobi followed by rental of private rooms. The number of active Airbnb rentals will therefore be considered from April 2012 to March 2023 as captured in Airbnb.com. Airbnb price dispersion was measured in terms of the monthly ADR for all the listed Airbnb rentals within the study period. Price differentials was computed as the variance between hotel monthly ADR and Airbnb rental monthly ADR. Monthly average figures were considered. Data sources for the ADR were compared and where there was variation, the average value of the data sources was considered.

The dependent variable for this study is hotel performance measured in terms of RevPAR. Monthly RevPAR data in this case was computed by multiplying hotel monthly ADR and monthly average occupancy rate data obtained from annual government reports. Again, where there was variation in the data sources, the study considered the average values.

3.6 Model Estimation

There are four common models used in panel data analysis, namely the difference-in-difference (DID) model, the fixed effects model, the pooled OLS model, and the random effects model (Xu et al., 2007; Torres-Reyna, 2007). According to Xu et al. (2007), DID is useful in situations where the panel data have only two time periods. The fixed effect model is used when it’s clear that individual characteristics of explanatory variables affect the regressors while random effect is applicable there are reasons to believe that individual characteristics of explanatory variables are uncorrelated with the dependent variables (Torres-Reyna, 2007). First, a combination of econometric models was used to estimate the main effect of Airbnb supply, price differentials, and Airbnb price dispersions on the RevPAR of star-rated hotels in Nairobi County. However, both fixed effects and random effects were ruled out as the two models did not turn out to be significant. This could be attributable to the pooled nature of the panel data used. The study therefore used Pooled OLS regression analysis

Hotel RevPAR *i* at time *t* was therefore modelled as a function of Airbnb listing numbers, Airbnb price differentials and Airbnb price dispersion as shown in equation 1.

$$RevPAR_{it}=\beta_0+ \beta AirbnbNum_{it}+ \beta PriceDiff_{it}+\beta AirbnbDisp_{it}++\varepsilon_{it} \tag{1}$$

Whereby:

$RevPAR_{it}$ denotes revenue per available room of a hotel at any given time

β_0 – Constant

$AirbnbNum_{it}$ denotes quantity of active Airbnb rentals in Nairobi at time t,

$PriceDiff_{it}$ denotes the *Price Differentials at time t*

$AirbnbDisp_{it}$ stands for Airbnb price dispersion

ε_{it} is the error term.

While there are a number of tools such as STATA, Eviews and Gretl, for econometric analysis, this current study used STATA Version 13 for model estimation because of its wider acceptance in econometrics analysis (Muenchenm, 2012).

3.7 Reliability and Validity

Data for this study were obtained from published annual government reports that are in the public domain and therefore are verifiable. Data from AirDNA are also generated on a monthly basis based on factual data obtained from Airbnb hosts and are therefore available on request from AirDNA. Similar data are also published by Airbitics and Inside Airbnb and are fairly comparable. Airbnb Listing data were obtained from Airbnb.com which is also publicly available and verifiable. Furthermore, diagnostic tests including normality, multicollinearity, autocorrelation, and heteroscedasticity were performed to ensure that the data met the basic assumptions of the classical linear regression model (CLRM).

3.8 Diagnostic Tests

3.8.1 Normality Test

To test for normality, this study used a variation of Jarque Bera Test, skewness and kurtosis to assess univariate normality. This was considered because the study cases were fewer i.e., 132 to apply Jarque Bera Test which requires larger cases or samples over 600 cases. The study first analysed the skewness and kurtosis of the variables for assessment. It then computed residuals of the variables and conducted skewness and kurtosis test on the same. Both results in Figure 3.2 indicated that there were univariate normality issues on the data set as evidenced by the chi^2 $p < 0.05$, which were also less than their corresponding adjusted Chi^2 values (Wulandari, Sutrisno & Nirwana, 2021).

Skewness/Kurtosis tests for Normality

				joint	
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
RevPAR	132	0.0002	0.9798	11.70	0.0029
AirbnbList~s	132	0.0046	0.0000	23.76	0.0000
PriceDiff	132	0.0000	0.0018	24.09	0.0000
AirbnbADR	132	0.0042	0.0395	10.69	0.0048

Figure 3.2: Skewness/Kurtosis tests for normality results from STATA

According to Wulandari et al. (2021), test for univariate normality is not adequate in a multivariate analysis as in this study. With multivariate examination, there is a need to also address multivariate normality. This study assessed multivariate normality using Mardia statistics, Henze-Zirkler test and Doornik-Hansen (Wulandari et al., 2021) as shown in Figure 3.3. Like in the univariate normality test, data is said to be multivariate normal when the Chi^2 $p > 0.05$.

```
Test for multivariate normality

    Mardia mSkewness =  6.115824    chi2(20) =  138.859   Prob>chi2 =  0.0000
    Mardia mKurtosis =  25.97127     chi2(1) =    2.672   Prob>chi2 =  0.1022
    Henze-Zirkler    =  4.696934     chi2(1) =  213.451   Prob>chi2 =  0.0000
    Doornik-Hansen                   chi2(8) =  107.922   Prob>chi2 =  0.0000
```

Figure 3.3: Test for multivariate normality

The results indicate that multivariate normality was an issue given that all the Chi^2 $p < 0.05$, which were also less than their corresponding adjusted Chi^2 values (see Table 2) in each of the test used. Normality of the data was also assessed graphically using Q-Q plots is STATA by plotting residuals against inverse normal. The residuals stray away from the 45-degree line in the Q-Q plot in Figure 3.4, indicating that the data set is not normally distributed. All the tests conducted, both statistical and graphical shows that the pooled panel data set in not normally distributed and therefore needed to be corrected before subjecting it to pooled regression analysis.

When normality of the data set is violated, different methods to handling non-normal data have been proposed. They include invoking the Central Limit Theorem (CLT), data transformation e.g., generating logs, bootstrapping, trimming the data, using non-parametric approaches based on rank, such as the sign test, winsorizing the data, using heteroscedastic consistent covariance matrices (HCCMs), invoking robust regression analysis or application of logistic regression and other nonlinear models (Pek, Wong & Wong, 2018). Despite the fact that the application of CLT remains within the linear modelling framework, it requires larger sample sizes (Pek, Wong and Wong, 2017b; Pek et al., 2018) which wasn't the case in this study. The rest with exception of bootstrapping do not lie within the linear modelling framework (Pek et al., 2018). While transformation is the widely used technique to solving non-normality followed by bootstrapping, its major challenge comes with obfuscation of variable interpretation (Pek et al., 2018; Sainani, 2012). This study used the robust standard error (SE) regression analysis option since it allowed the data to be retained in their original units without making any major changes to it (Pek et al., 2018; Sainani, 2012).

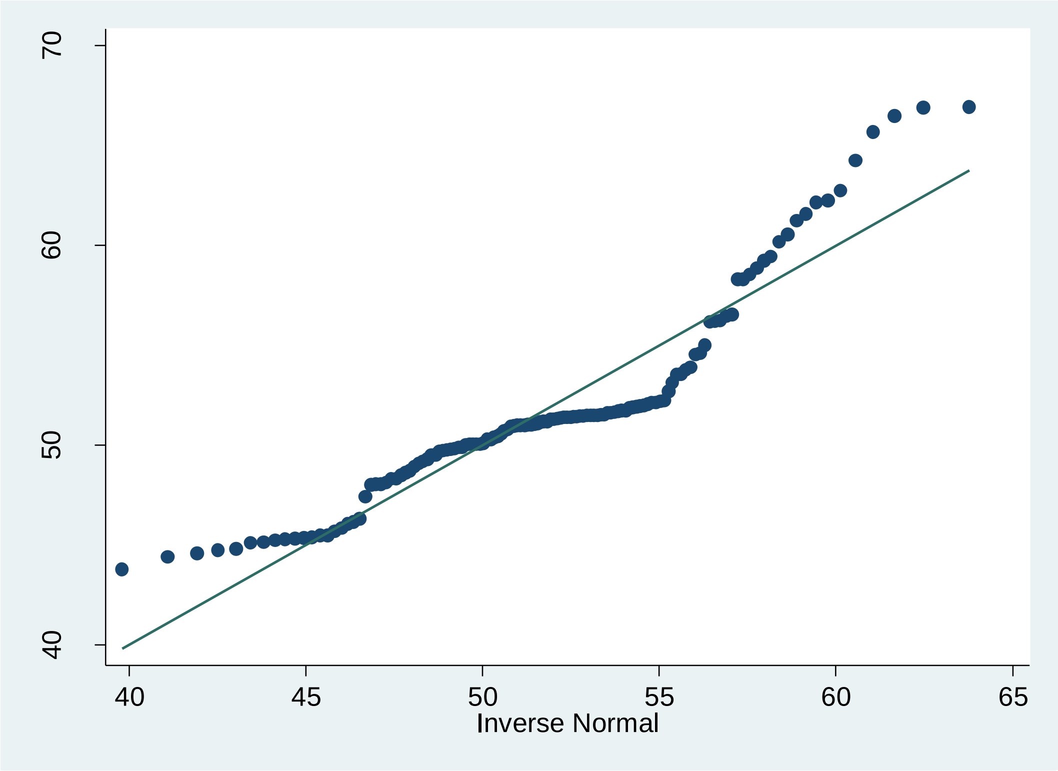

Figure 3.4: Q-Q plots of residuals vs inverse normal

3.8.2 Multicollinearity Test

In this study, the variance inflation factor (VIF) was used to assess the multicollinearity among the independent variables, with VIF values greater than 3 indicating a collinearity problem (Hair et al., 2020; Hair et al., 2022). Figure 3.5 shows that the VIF values were < 3 ranging between 1.30 in respect of Airbnb Listings and 1.14 in respect of price differentials, indicating that multicollinearity wasn't a problem.

```
. vif
```

Variable	VIF	1/VIF
PriceDiff	2.14	0.467413
AirbnbADR	1.77	0.565533
AirbnbList~s	1.30	0.767245
Mean VIF	1.74	

Figure 3.5: VIF multicollinearity results from STATA

3.8.3 Heteroscedasticity

When the variance of the residuals is unequal across a range of measured values, this is referred to as heteroskedasticity or heteroscedasticity. The opposite is homoskedasticity which indicate that the equal residual variance across the range of measured values in a population. Both Breusch-Pagan / Cook-Weisberg test and White test were conducted to assess for heteroskedasticity. The study also used graphical analysis by generating scatter plot for residual and fitted values. The null hypothesis in both tests (see Figure 3.6 and Figure 3.7) indicates the presence of constant variance, indicating that the data is homoscedastic.

```
. hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of RevPAR

         chi2(1)      =    17.63
         Prob > chi2  =   0.0000
```

Figure 3.6: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity STATA results

However, the p values in both tests are < 0.05 and significant enough to reject the null hypotheses, an implication that there is heteroscedasticity in the residuals.

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(9)      =     50.27
         Prob > chi2  =    0.0000

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	50.27	9	0.0000
Skewness	12.52	3	0.0058
Kurtosis	5.77	1	0.0163
Total	68.56	13	0.0000

Figure 3.7: White test for heteroskedasticity STATA results

Graphical analysis as shown in Figure 3.8 also indicates presence of heteroskedasticity in the data set.

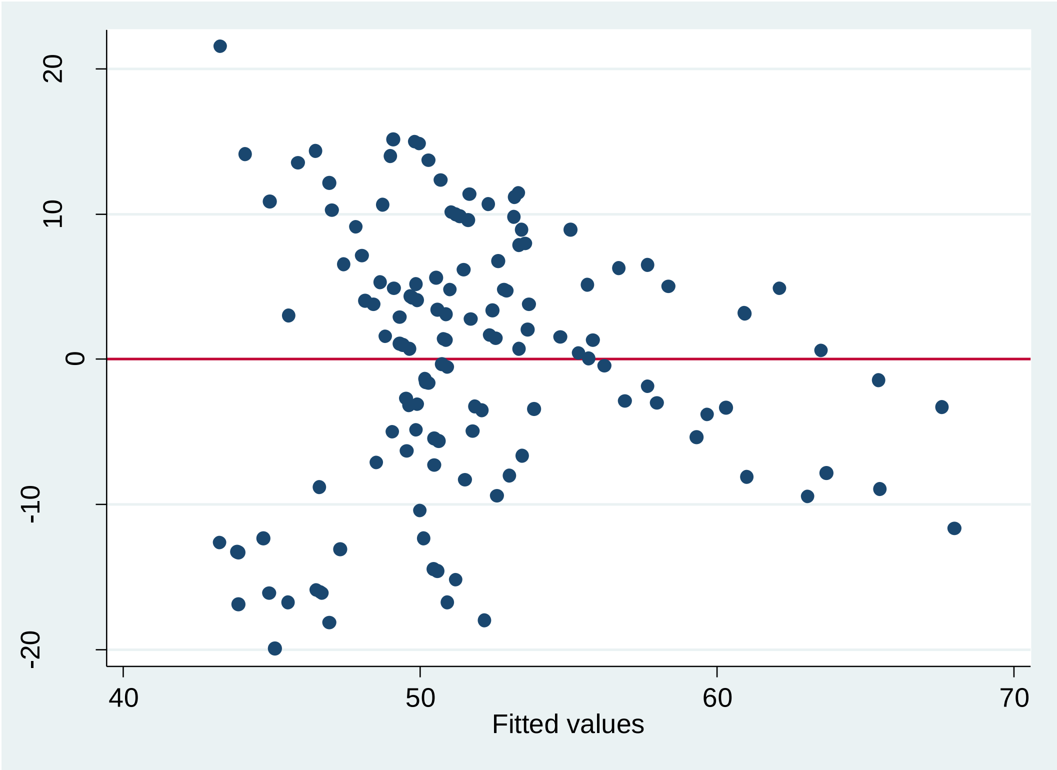

Figure 3.8: Residuals versus fitted plot for heteroscedasticity test results from STATA

Heteroskedasticity in this case could be due to model misspecification, measurement error, or subpopulation differences, implying that the OLS estimates Best Linear Unbiased Estimator (BLUE), causing bias in test results and confidence intervals (Sajwan & Chetty, 2018).

3.8.4 Autocorrelation

When error terms in a regression model correlate over time or are dependent on each other, an autocorrelation problem occurs (Sajwan & Chetty, 2018). Autocorrelation in pooled panel regression analysis can be assessed using the classical Durbin Watson's statistics or the Breusch-Godfrey LM test in STATA. According to Sajwan and Chetty (2018), Durbin-Watson test is based on the assumption that the residual distribution is normal, whereas the Breusch-Godfrey LM test is less dependent on this assumption. Both tests were used in this study to assess for autocorrelation.

Breusch-Godfrey LM test for autocorrelation as shown in Figure 3.9 indicates that $Chi^2 < 0.05$ implying that the notion of lack of serial correlation is not true. It suggests that there is autocorrelation between the residuals in the model.

```
. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
1	73.505	1	0.0425

```
H0: no serial correlation

Durbin-Watson d-statistic (4, 132) = 1.857749
```

Figure 3.9: Durbin Watson's statistic results from STATA

Durbin Watson's statistic ranges from 0 to 4. A value < 2 indicates positive autocorrelation, values = 2 indicate lack of autocorrelation while values > 2 indicate negative autocorrelation (Sajwan & Chetty, 2018). The result of the Durbin-Watson d-statistic (4, 132) = 1.858 is < 2, an indication of positive autocorrelation (see Figure 3.8). As a result, there was a need to correct for autocorrelation.

3.8.5 Joint Effect of Months as a Dummy Variable

The study used pooled panel data from April 2012 to March 2023 and as a result, there was a need to determine joint effects of time variable (months) on the cross-sectional variables namely RevPAR, price differentials, Airbnb price dispersion and Airbnb listings. To achieve this, monthly dummy variable was generated in STATA and included in the regression model in STATA. Its joint effect was then assessed by running the syntax *testparm month.* Results are presented in Figure 3.9.

Results in Figure 3.9 show that month as a time variable doesn't have significant effect on hotel RevPAR ($\beta = .325$, $t = 1.39$, $p > .05$). Thus, the total effect of the time variable (months) is zero. The *testparm* results ($p = .167$) further indicate that pooled regression is free of the joint effect of the time variable (months) given $P > .05$. It implies that the pooled panel data set in this case does not include the variables due to the month distinction, and that the data lacks any sort of fixed effects. Pooled regression analysis is, therefore, applicable in this data set.

```
. reg RevPAR AirbnbListings AirbnbADR PriceDiff month

      Source |       SS       df       MS              Number of obs =     132
-------------+------------------------------           F(  4,   127) =    9.93
       Model |  3345.90456     4  836.476139           Prob > F      =  0.0000
    Residual |  10693.4396   127  84.2003122           R-squared     =  0.2383
-------------+------------------------------           Adj R-squared =  0.2143
       Total |  14039.3442   131  107.170566           Root MSE      =  9.1761

------------------------------------------------------------------------------
      RevPAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
AirbnbListings |  -.0168215   .0051293    -3.28   0.001    -.0269714   -.0066715
   AirbnbADR |  -.2763657   .0641511    -4.31   0.000    -.4033092   -.1494223
   PriceDiff |  -.3010706   .0506373    -5.95   0.000    -.4012726   -.2008685
       month |   .3247194   .2335725     1.39   0.167    -.1374784    .7869172
       _cons |    102.734   9.229804    11.13   0.000     84.46989    120.9981
------------------------------------------------------------------------------

. testparm month

 ( 1)  month = 0

       F(  1,   127) =    1.93
            Prob > F =    0.1669
```

Figure 3.10: Pooled regression analysis with month for joint effect analysis

3.9 Pooled Panel Regression Analysis

Given that the pooled panel data presented issues of autocorrelation, normality and heteroskedasticity, there was a need to correct for all these before deciding on the final pooled regression model. To correct for heteroskedasticity in pooled panel data regression analysis, Sajwan and Chetty (2018) proposes change of functional form or using robust regression analysis option. This study adopted the latter approach by conducting robust pooled regression analysis to correct for heteroskedasticity, autocorrelation and normality. To achieve this, a series of pooled regression analysis were conducted in STATA, with each correcting the diagnostic issues that emerged before final interpretation. The results are presented in Chapter Four.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

This chapter presents the findings of the study and discusses them. The chapter begins with a description of the study variables in the form of trend analysis using graphs. It then provides the results and discussions of regression analysis in line with the study objectives and hypotheses.

4.1 Descriptive Statistic Results

Descriptive analysis of frequencies indicates entire home rental accounts for 75% of active Airbnb rentals in Nairobi County followed by private rooms at 23% as shown in the pie chart in Figure 4.1.

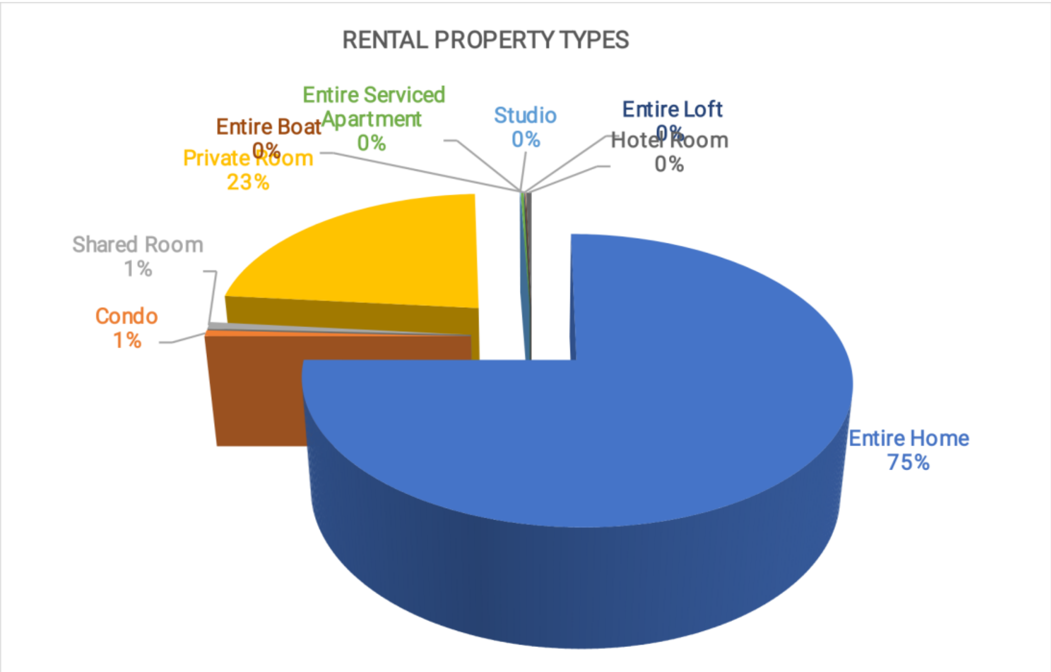

Figure 4.1: Airbnb rental types in Nairobi County as at March 2023

Trend analysis of both hotel bed occupancy and RevPAR has been fluctuating with major troughs experienced between 2020 and 2021 as illustrated in Figures 4.2 and 4.3. This could be attributable to Covid-19 pandemic.

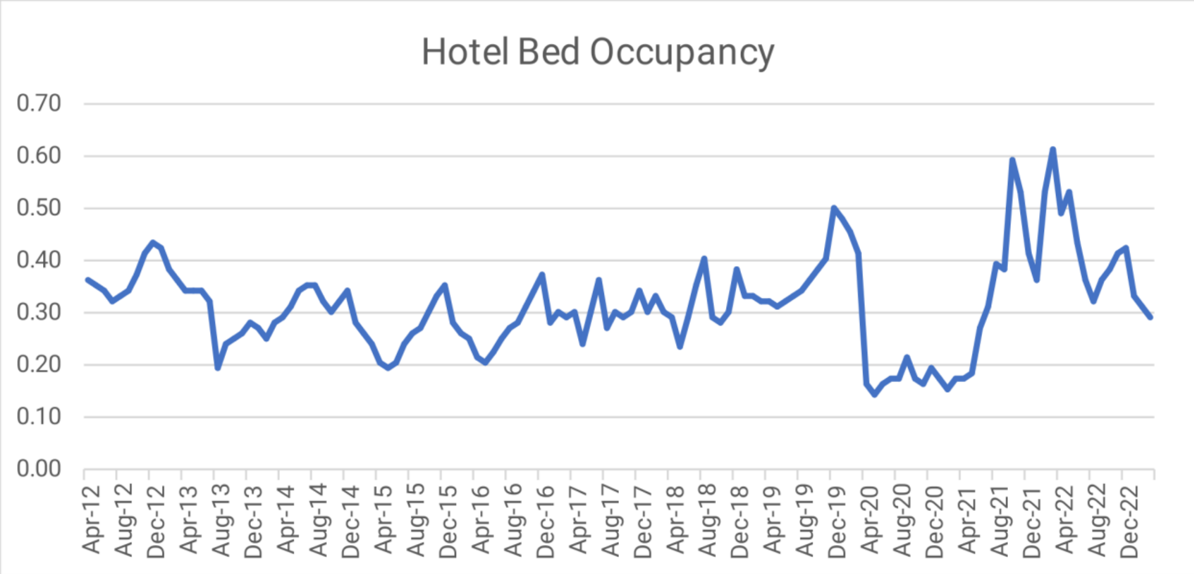

Figure 4.2: Hotel bed occupancy trend in Nairobi County between April 2012 and March 2023

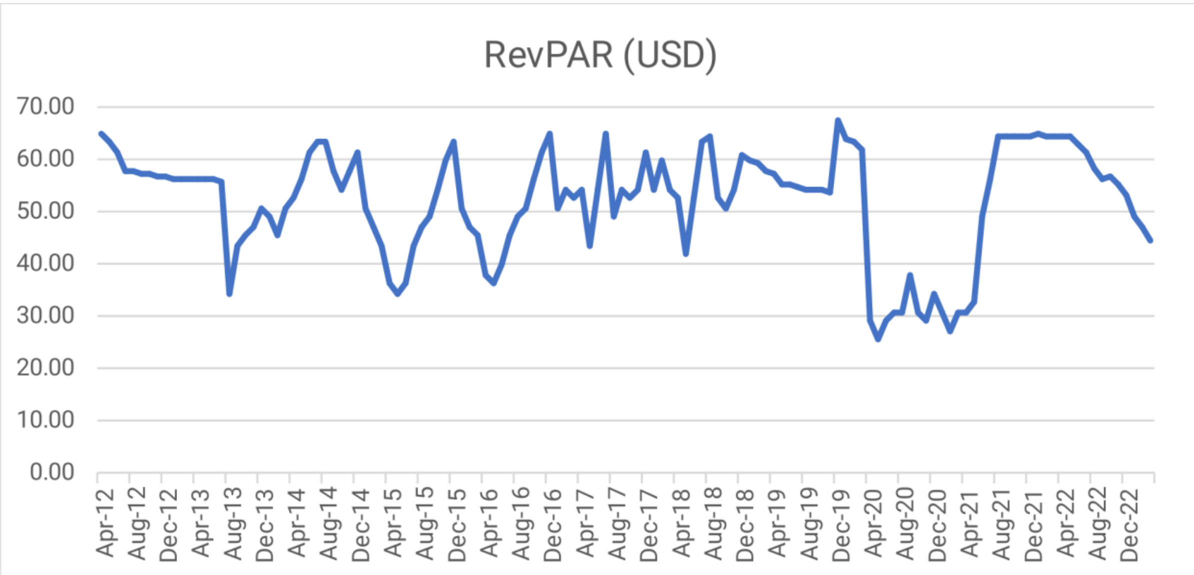

Figure 4.3: Hotel RevPAR trend in Nairobi County between April 2012 and March 2023

The results as shown in Figure 4.4 indicate that there has been an exponential increase in Airbnb listings from April 2012 to March 2023 with major exponential increase beginning to be recorded in 2016.

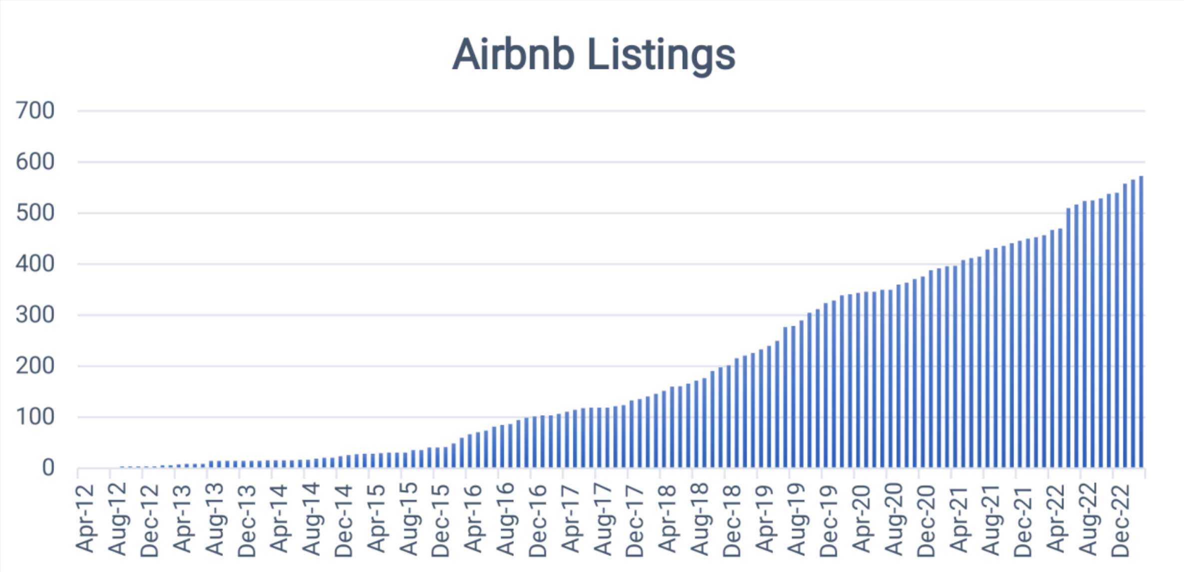

Figure 4.4:Airbnb listings in Nairobi County between April 2012 and March 2023

Figure 4.5 depicts a combined analysis of the two variables, Airbnb listings and hotel RevPAR of star rated hotels in Nairobi County.

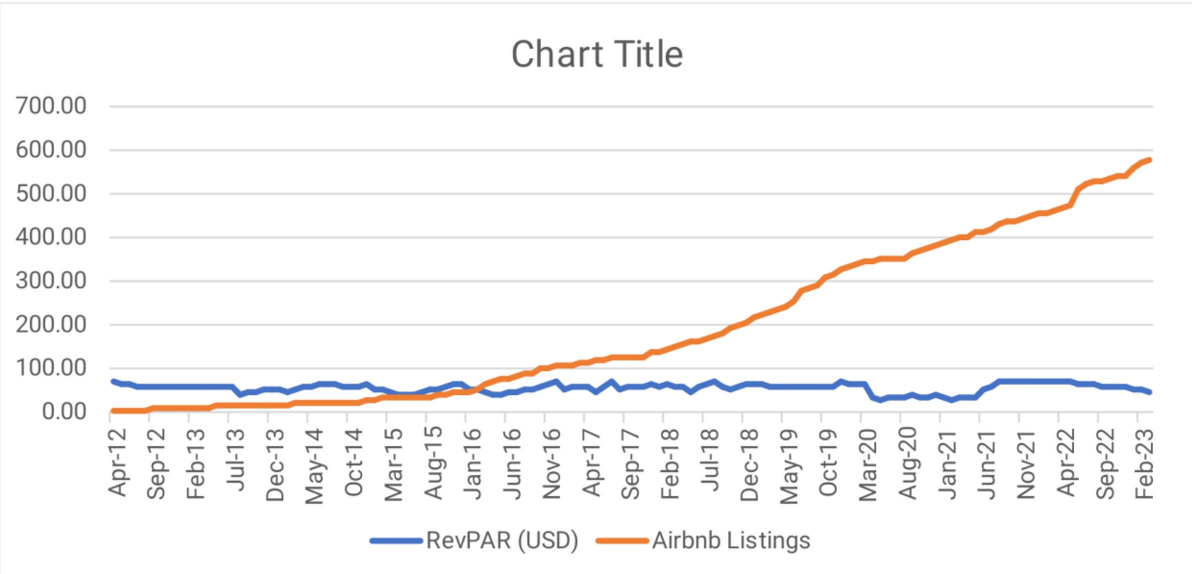

Figure 4.5: The trend of Hotel RevPAR and Airbnb listings between April 2012 and March 2023

It shows that up to a round January 2016, Airbnb supply wasn't a concern for star-rated hotels in Nairobi County since minimal impact if any could be witnessed on hotel RevPAR. However, beyond 2016, RevPAR for hotels is generally on the downward trend as Airbnb listings keep on increasing, although this could also be attributable to other factors.

4.2 Pooled OLS Regression Analysis Results

The study was designed to look into the effects of Airbnb penetration on RevPAR of star-rated hotels in Nairobi County. To actualise the specific research objectives as stated in Chapter One, the following null hypotheses were postulated.

> H_{01}: Airbnb listings does not have a significant effect on RevPAR of star-rated hotels in Nairobi County
>
> H_{02}: Airbnb price differentials does not have a significant effect on RevPAR of star-rated hotels in Nairobi County
>
> H_{03}: Airbnb price dispersion does not have a significant effect on RevPAR of star-rated hotels in Nairobi County

To test the hypotheses, a series of pooled OLS regression analysis was conducted and the results are depicted in Figures 4.6 through 4.8. The results of the original pooled OLS results without correction for normality, heteroscedasticity and autocorrelation are shown Figure 4.6, while Figure 4.7 shows the result after correction for heteroscedasticity and normality.

The results are fairly similar in both cases with both models being significant ($p < .05$) but slight variations in the F values, standard errors, t values and p values. Both models show that Airbnb listings, Price differentials and Airbnb price dispersions accounts for 22.7% (R^2 = .227) of variation in RevPAR of star-rated hotels.

```
. xi: regress RevPAR AirbnbListings AirbnbADR PriceDiff

      Source |       SS       df       MS              Number of obs =     132
-------------+------------------------------           F(  3,   128) =   12.51
       Model |  3183.16734     3  1061.05578           Prob > F      =  0.0000
    Residual |  10856.1769   128  84.8138817           R-squared     =  0.2267
-------------+------------------------------           Adj R-squared =  0.2086
       Total |  14039.3442   131  107.170566           Root MSE      =  9.2094

------------------------------------------------------------------------------
      RevPAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
AirbnbListings |  -.0172835   .0051371    -3.36   0.001    -.0274482   -.0071188
   AirbnbADR |  -.2755596   .0643818    -4.28   0.000    -.4029499   -.1481692
   PriceDiff |  -.3079394   .0505789    -6.09   0.000    -.4080185   -.2078603
       _cons |   105.7269   9.007878    11.74   0.000     87.90323    123.5505
------------------------------------------------------------------------------
```

Figure 4.6: Original pooled panel data regression analysis results from STATA

```
. reg RevPAR AirbnbListings AirbnbADR PriceDiff, vce(robust)

Linear regression                               Number of obs =       132
                                                F(  3,   128) =     16.69
                                                Prob > F      =    0.0000
                                                R-squared     =    0.2267
                                                Root MSE      =    9.2094

------------------------------------------------------------------------------
             |               Robust
      RevPAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
AirbnbListings |  -.0172835   .0061694    -2.80   0.006    -.0294907   -.0050763
   AirbnbADR |  -.2755596   .0609058    -4.52   0.000    -.3960721    -.155047
   PriceDiff |  -.3079394   .0495492    -6.21   0.000     -.405981   -.2098979
       _cons |   105.7269    8.73549    12.10   0.000      88.4422    123.0115
------------------------------------------------------------------------------
```

Figure 4.7: Pooled OLS results from STATA after correction for normality and heteroscedasticity

However, the results cannot be interpreted in their current form as autocorrelation is still an

```
prais RevPAR AirbnbListings PriceDiff AirbnbADR, corc

Iteration 0:  rho = 0.0000
Iteration 1:  rho = 0.4396
Iteration 2:  rho = 0.4913
Iteration 3:  rho = 0.4945
Iteration 4:  rho = 0.4947
Iteration 5:  rho = 0.4947
Iteration 6:  rho = 0.4947

Cochrane-Orcutt AR(1) regression -- iterated estimates

      Source |       SS       df       MS              Number of obs =     131
-------------+------------------------------           F( 3,    127) =   10.34
       Model |  235.703276     3  78.5677588           Prob > F      =  0.0000
    Residual |  4260.0327    127  33.5435646           R-squared     =  0.2242
-------------+------------------------------           Adj R-squared =  0.2041
       Total |  4495.73598   130  34.5825845           Root MSE      =  5.7917

------------------------------------------------------------------------------
      RevPAR |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
AirbnbListings |  -.0171657   .0031143   -2.14   0.034     -.0336145     -.00568
   PriceDiff |  -.1255781    .047532   -2.64   0.009     -.2196354    -.031520
   AirbnbADR |   -.116426   .0510118   -2.28   0.024     -.2173691    -.015482
       _cons |   73.35992   9.080652    8.08   0.000      55.39095     91.3288
-------------+----------------------------------------------------------------
         rho |   .4946669
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.857749
Durbin-Watson statistic (transformed) 1.987789
```

Figure 4.8: Pooled regression results from STATA after correction of heteroscedasticity and autocorrelation

The model indicates that Airbnb listings, price differentials and Airbnb price dispersions account for 22.4% (i.e., $R^2 = .224$) of the variation in RevPAR of star-rated hotels in Nairobi County. The results show that all the predictors namely Airbnb listings, price differentials and Airbnb price dispersions had significant effect on RevPAR of star-rated hotels in Nairobi County ($F [3, 127] = 10.34$, $p < .001$, $R^2 = .224$). This means that the three predictors account for 22.4% of the variation in RevPAR of star-rated hotels in Nairobi County.

4.2.1 Effects of Airbnb Listings on RevPAR

The first research objective was to determine the effect of Airbnb listings on RevPAR of star-rated hotels in Nairobi County. To actualise this objective, it was hypothesised that Airbnb listings does not have a significant effect of RevPAR of star-rated hotels in Nairobi County. Airbnb listings relates the numbers of Airbnb rental supply in Nairobi County as listed in Airbnb.com. Descriptive analysis suggests that Airbnb supply in Nairobi County doesn't cause concern among hoteliers between 2012 when it was first introduced in Nairobi and 2016. This supports Mody and Gomez (2018) who contend that during its initial stages of influx, Airbnb rentals doesn't cause jitters among hoteliers due to the notion that it serves a different market segment. However, from 2016 onwards, the findings suggests that Nairobi County started experiencing increased influx of Airbnb rental facilities. The regression results indicates that Airbnb listings had a significant negative effect on RevPAR of star-rated hotels in Nairobi County ($\beta = -.017$, $t = -2.14$, $p = .034$). This imply that a percentage increase in Airbnb supply within Nairobi County will reduce RevPAR of hotels by about .017%. The null hypothesis was therefore rejected. These findings imply that with increased number of active Airbnb rentals, the travelling public is presented with options of fairly cheap accommodation facilities for their use which is accessed through peer-to-peer platforms at their convenience. In doing so, they would shun conventional hotel rooms which are perceived to be expensive. This in turn would reduce hotel occupancy and affects their RevPAR.

The study findings corroborate findings of Dogru et al. (2020) who conducted a similar study in Paris, Sydney, London and Tokyo and found that increase in Airbnb supply within these markets decreased the RevPAR of hotels in the said markets by between 0.016% and 0.031%. The findings are also in line with other similar studies such as Dogru et al. (2017b) and Zervas et al. (2017). In Boston, for example, Dogru et al. (2017b) discovered that a percentage rise in Airbnb availability reduced hotel RevPAR by .025%. Likewise, a percentage upsurge in Airbnb supply in Texas reduced hotel RevPAR by .04% (Zervas et al., 2017). The study further supports a similar study conducted in US between 2008 and 2017 by Dogru et al. (2018). They concluded that an increase in the supply of Airbnb resulted in a decreased RevPAR of between 2% to 4% across hotel segments in the US markets. The findings of the current study however, contradict those of other researchers (Euromonitor International, 2013; STR, 2016a, 2016b; Choi et al., 2015; Morgan Stanley Research, 2015; Haywood et al., 2017) who contend that Airbnb rentals poses no significant threat to hotel RevPAR. For example, Blal et al. (2018), reported that overall hotel RevPAR is not in any way related to total Airbnb supply in San Francisco. Similarly, Choi et al. (2015), in their study concluded that Airbnb rentals has no significant effect on revenues of Korean hotels.

4.2.2 Effects of Price Differentials on RevPAR

The second research objective was to assess effect of price differentials on RevPAR of star-rated hotels in Nairobi County. It was therefore, postulated that price differentials do not have a significant effect of RevPAR of star-rated hotels in Nairobi County. Price differential is the difference in room rates between the star-sated hotels and the Airbnb rentals. The study findings indicate that price differential had a significant negative effect on RevPAR of star-rated hotels in Nairobi County ($\beta = -.126$, $t = -2.64$, $p = .009$). The study results indicate that a percentage increase in price differential would result to a decrease in RevPAR of star-rated hotels by .13%. This means that, the bigger the difference in rates charged between the hotels and Airbnb as a result of hotel charging higher rates, the lesser revenue generated by hotels from the room sales. Clients would prefer accommodation facilities charging lower rates as opposed to those charging higher rates provided their service expectations are met.

The findings support sentiments by other researchers (e.g., Xie and Kwok, 2017) that RevPAR is not only a function of Airbnb supply but also other contextual factors including price factors, especially when they are perceived from a competitive point of view rather than a supplementary point of view.

4.2.3 Effects of Airbnb Price Dispersions on RevPAR

The last research objective focused on identifying effects of Airbnb price dispersion on RevPAR of star-rated hotels in Nairobi County. It was, therefore, hypothesised that Airbnb price dispersion does not have a significant effect on RevPAR of star-rated hotels in Nairobi County. The results indicate that Airbnb price dispersion had a significant negative effect on RevPAR of star-rated hotels in Nairobi County ($\beta = -.116$, $t = -2.28$, $p = .024$), and as such the null hypothesis was rejected. These findings imply that a percentage increase in Airbnb price dispersion would decrease RevPAR of star-rated hotels in Nairobi County by .12%. Different Airbnb rental facilities charges different rates. Airbnb rental facilities are however, believed to charge lower rates so that they become attractive to their clients who are price conscious. Those Airbnb rental facilities charging lower prices and offering quality services would therefore be preferred by guests compared to those charging higher rates closer to what the hotels are charging. A larger dispersion means variations in the charges. With clients preferring facilities charging lower rates, there would be higher demand for these facilities compared hotels and those Airbnb charging higher rates. Hotels would attract fewer customers with would affect their occupancy rate as well as ADR. In the long run, hotels will be forced to reduce their rates in order to increase their occupancy rate. With reduced rates, revenues would also go down. Hotels that choose not to reduce their rates would still be affected because of low occupancy rate which in turn would affect their revenues. The findings differ with Xie and Kwok (2017) who found that Airbnb price dispersion had a positive effect on hotels RevPAR. Xie and Kwok (2017) however, examined this from a moderation perspective

CHAPTER FIVE
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study adopted the disruptive innovation theory to look into the impact of Airbnb penetration on RevPAR of star-rated hotels in Nairobi County. Pooled panel data was for the period between April 2012 and March 2023 was collected from AirDNA, Airbnb.com and government reports. The data related to Airbnb listings, occupancy rates, ADR and RevPAR collected from 54 star-rated hotels and 12,336 Airbnb rental facilities in Nairobi County. Data was prepared and subjected to descriptive analysis in excel and Pooled OLS regression analysis in STATA. Regression results indicated that Airbnb penetration through listings, price differentials and price dispersion explain about 22.42% of the variation in RevPAR of star-rated hotels in Nairobi County.

The first research objective was to determine the effect of Airbnb listings on RevPAR of star-rated hotels in Nairobi County. The descriptive results of the study generally indicate that initially, Airbnb listings have no discernible effect on performance of star-rated hotels in Nairobi County. Regression result indicates that Airbnb listings negatively affect RevPAR of star-rated hotels in Nairobi County, hence the null hypothesis was found to be false. The implication of the study is that influx of Airbnb in Nairobi County draws away potential clients of star-rated hotels which affects their occupancy rate and in turn RevPAR. This is attributable to the perception that Airbnb rental facilities charge less for their rooms in comparison to conventional hotels and also that guest can easily make reservations conveniently through the Airbnb peer-to-peer platform.

Second objective of the study was concerned with assessment of the effect of price differentials on RevPAR of star-rated hotels in Nairobi County. The current study's findings indicate that price differentials negatively affect RevPAR of star-rated hotels in Nairobi County, leading to rejection of the null hypothesis. Price differential was computed as the difference between average room rates of star-rated hotels and average room rates of Airbnb rental facilities. The findings imply that the wider the difference, the negatively affected the RevPAR of star-rated hotels is. Hotel RevPAR would be negatively affected because guest would prefer Airbnb rental facilities that charge lower rates in comparison to hotels which would affect occupancy rates and eventually RevPAR of the hotels.

The final research objective was to determine effect of Airbnb price dispersions on RevPAR of star-rated hotels in Nairobi County. The findings revealed that Airbnb dispersion had a significant negative effect on RevPAR of star-rated hotels in Nairobi County, hence the null hypothesis was rejected. Price dispersion is the variations in prices charged by different Airbnb rentals. When this variation is big, it means that the hotels would be affected negatively due to preference of facilities charging lower rates. With most Airbnb rental facilities charging lower rates, hotels and other facilities charging higher rates may be forced to lower their prices which would in turn reduce their revenues.

5.2 Recommendations

5.2.1 Recommendations to Practitioners

Penetration of Airbnb rentals in Nairobi County is a significant game changer in the long run with such influx affecting hotel performance financially. While the Airbnb was believed to target a different market segment from what the conventional hotels targets, the reality is that majority of the clients have developed tendency to prefer Airbnb due to the convenience it offers. On this premise, the study recommends that:

1) Hoteliers in Nairobi County should not only be concerned with the numbers of Airbnb supply, but should also closely monitor price factors such as Airbnb price dispersions and price differentials as these have got higher negative implications on their revenues.
2) The study also recommends that the proprietors of star-rated hotels in Nairobi County and other parts of Kenya need to take advantage of this disruptive innovation and use it as another distribution channel platform for their hotel rooms to improve their performance over time.

5.2.2 Recommendations for Future Research

This study did not factor in other aspects of the hotels such as location, and age which could be cofounding factors on the effect of Airbnb on RevPAR of star-rated hotels. This study, therefore, suggests that other future studies can be done by incorporating hotel characteristics and the results compared with the current study findings.

The study also proposes extension of this current study to other destinations within the country such as Mombasa County where high proliferation of Airbnb has been witnessed, second to Nairobi County. The results can be compared to this study.

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APPENDICES

Appendix 1: Template for Pooled Panel Data Collection

Months	Hotels					Airbnb			
	Occup Rate	ADR (USD)	RevPAR (USD)	Rating		Listings	ADR (USD)	RevPAR	PriceDiff (Hotel ADR – Airbnb ADR)
Apr-2012									
May-2012									
Jun-2012									
Jul-2012									
Aug-2012									
Sep-2012									
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Feb-2018									

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Jan-2021									
Feb-2021									
Mar-2021									
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May-2022									
Jun-2022									
Jul-2022									
Aug-2022									
Sep-2022									
Oct-2022									
Nov-2022									
Dec-2022									
Jan-2023									
Feb-2023									
Mar-2023									

Appendix 2: Research Permit from NACOSTI

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Appendix 3: List of Star-Rated Hotels in Nairobi County as per TRA Listings

NO	ESTABLISHMENT	COUNTY	ROOMS	BEDS	RATING
1	Intercontinental Nairobi	Nairobi	326	372	*****
2	Radisson Blu Hotel Nairobi	Nairobi	271	354	*****
3	The Sarova Stanley	Nairobi	217	440	*****
4	Villa Rosa Kempinski	Nairobi	200	216	*****
5	Fairmont The Norfolk	Nairobi	170	200	*****
6	Sankara Nairobi	Nairobi	156	167	*****
7	The Boma Nairobi	Nairobi	148	178	*****
8	Crowne Plaza Nairobi Airport	Nairobi	144	209	*****
9	Tribe Hotel	Nairobi	137	154	*****
10	Dusit D2	Nairobi	101	122	*****
11	Hemingway's Nairobi	Nairobi	45	50	*****
12	Hilton Nairobi Limited	Nairobi	287	334	****
13	Crowne Plaza	Nairobi	206	254	****
14	Hilton Garden Inn Nairobi Airport	Nairobi	175	226	****
15	City Lodge Hotel at Two Rivers	Nairobi	171	200	****
16	Southern Sun Mayfair Nairobi	Nairobi	171	212	****
17	Eka Hotel	Nairobi	167	220	****
18	Sarova Panafric Hotel	Nairobi	162	324	****
19	Silver Springs Hotel	Nairobi	160	180	****
20	Nairobi Safari Club	Nairobi	146	186	****
21	The Panari Hotel, Nairobi	Nairobi	136	272	****
22	Ole Sereni Hotel	Nairobi	134	206	****

NO	ESTABLISHMENT	COUNTY	ROOMS	BEDS	RATING
23	Windsor Golf Hotel and Country Club	Nairobi	130	205	****
24	Fairview Hotel	Nairobi	127	133	****
25	Weston Hotel	Nairobi	120	154	****
26	Golden Tulip Westlands	Nairobi	94	188	****
27	Pride Inn Lantana	Nairobi	55	110	****
28	Best Western Executive Residency	Nairobi	48	106	****
29	House of Waine	Nairobi	11	20	****
30	Carnivore Restaurant	Nairobi	0	0	****
31	Ibis Styles Nairobi Westlands	Nairobi	277	331	***
32	Azure Hotel	Nairobi	165	231	***
33	Best Western Plus Meridian Hotel	Nairobi	128	166	***
34	Ngong Hills Hotel	Nairobi	110	165	***
35	The Heron Portico	Nairobi	109	218	***
36	Pride Inn Raptha Nairobi,	Nairobi	100	200	***
37	Sportsview Hotel Kasarani	Nairobi	94	188	***
38	Kenya Comfort Suits	Nairobi	88	120	***
39	La Masion Royale	Nairobi	71	144	***
40	The Clarion Hotel	Nairobi	62	67	***
41	Boma Inn Nairobi	Nairobi	59	83	***
42	Utalii Hotel	Nairobi	57	114	***
43	Marble Arch Hotel	Nairobi	41	57	***
44	Fahari Gardens Hotel	Nairobi	32	64	***
45	Villa Leone Guest House	Nairobi	51	54	***

NO	ESTABLISHMENT	COUNTY	ROOMS	BEDS	RATING
46	Jacaranda Hotel Nairobi	Nairobi	128	256	**
47	Town Lodge	Nairobi	84	124	**
48	Central Park Hotel	Nairobi	80	100	**
49	After 40 Hotel	Nairobi	63	101	**
50	Summerdale Inn	Nairobi	60	75	**
51	Eton Hotel	Nairobi	58	116	**
52	Zehneria Portico	Nairobi	56	65	**
53	Kahama Hotel	Nairobi	47	51	**
54	West Breeze Hotel	Nairobi	26	34	**