BEHAVIORAL ECONOMIC ANALYSIS OF TOURISM DEMAND

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Behavioral Economic Analysis of Tourism Demand

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CERTIFICATE OF ORIGINALITY

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LIN, Gabrielle

Abstract

Previous research, based on microeconomic demand theory from neoclassical economics, has established a quantitative framework for modeling tourism and hospitality demand. This framework, while insightful, has theoretical deficiencies and practical limitations. These include challenges in estimating dynamic elasticity across the full price range and in modeling disaggregate demand data. The latter is necessary to accurately capture the heterogeneous demand curves that vary across different consumers and contexts.

This thesis introduces a behavioral economic demand framework to tourism research, which offers several advantages over the neoclassical framework. It broadens the definition of price and demand to include non-monetary costs and valued entities, accounts for dynamic elasticity along the entire demand curve, and constructs complete demand curves to identify optimal pricing points. This framework allows for detailed micro-level analysis, revealing significant variability across different consumers and contexts. It incorporates behavioral heterogeneity by considering individual differences and environmental factors, leading to more accurate predictions of consumer behavior. These insights inform more effective pricing, marketing, and crisis management strategies, addressing many limitations of neoclassical models.

The thesis is structured in manuscript format, encompassing three sequential studies. The empirical studies within this thesis are contextualized specifically in the lodging sector, demonstrating the application of this novel methodology.

The first study offers a critical reflection on current issues in tourism demand modeling, examining both microeconomic demand theory and econometric demand models. It introduces and adapts the behavioral economic demand framework to the tourism context, developing a new conceptual model for disaggregate level tourism demand modeling.

The second study serves as an empirical application of the conceptual model proposed in the first study. It constructs disaggregate demand curves for three hotel types (economy, midscale and upscale) using a behavioral economic demand model. This study reveals the heterogeneity of demand curves across various consumer demographics (including gender, age, income, preference and risk tolerance) and different contexts (such as normal situations versus pandemic situations).

The third study delves into the application of the behavioral economic demand framework in analyzing product interactions. It constructs both alone-price and own-price demand curves for three hotel types (economy, midscale and upscale), as well as cross-price demand curves for sharing accommodation in relation to hotel pricing. This aims to quantify the dual-directional substitutive relationship between hotels and sharing accommodation. Additionally, it explores the varying degrees of substitutability between different customer groups (segmented by gender, age and preference) and travel companion scenarios (traveling alone versus traveling with friends).

This thesis is the first to introduce the behavioral economic demand framework into tourism research. It offers an innovative theoretical framework for understanding and analyzing demand curves, advancing the interpretation of elasticity with a focus on the dynamic nature of elasticity along the demand curve. This approach elevates tourism demand modeling to a more comprehensive and micro-oriented level. Utilizing behavioral economic demand models to construct complete demand curves enables researchers to gain a thorough understanding of the interplay between price, demand and revenue. This level of insight has not been achieved by most econometric modeling studies. Moreover, the complete demand curves serve as a functional tool for analyzing substitutive and complementary relationships between products. The methodology also provides flexibility in collecting and processing disaggregate demand data. This thesis demonstrates that modeling tourism demand at the disaggregate level can reveal many more details about demand that have been overlooked by previous demand modeling practices.

The research findings have multiple implications for managerial decision-making. The complete demand curve indicates the optimal pricing point for maximizing business revenue. It also highlights variations in this optimal pricing point across different consumer groups and consumption scenarios. Furthermore, disaggregate demand curves can aid businesses in developing differentiated sales strategies tailored to various customer segments, as well as in devising appropriate responses to health crises. Additionally, a thorough investigation of the substitution between different hotel types and sharing accommodation can inform effective competition strategies for each type of lodging establishment.

Keywords

Behavioral economics, Demand modeling, Demand curve, Disaggregate, Tourism, Hotel

Publications Arising from the Thesis

Lin, G., Chen, J. L., Li, G., & Song, H. (2024). Substitution between sharing accommodation and hotels: A behavioral economic demand curve analysis. *Annals of Tourism Research*, *104*, 103716. https://doi.org/10.1016/j.annals.2023.103716 (Chapter 4)

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Chapter 1 Introduction

In economics, demand analysis is a fundamental component that informs the decisions of both private and public economic agents. A deep understanding of consumers' decision-making processes, achieved through rigorous demand analysis, can facilitate the development of effective business strategies and efficient public policies. To simplify complex economic activities within a unified quantitative framework, economists commonly employ demand models to describe the relationships between demand and its determinants.

Demand analysis holds similar importance in the hospitality and tourism industry. Since its emergence in the mid-19th century (Brendon, 1991), the modern tourism industry has experienced significant growth. The consumption of tourism products has increasingly become a notable component of consumer expenditure budgets. This not only enhances consumer well-being but also contributes positively to the broader economy, impacting factors such as income levels, employment rates, fiscal revenue, environmental awareness and cultural exchange (Stabler et al., 2010). As a sector rich in human and business interactions, tourism encompasses extensive economic activities across various sectors, including accommodation, transportation, food and beverage, and tourist attractions. In each sector, consumer demand plays a vital role in shaping corporate profitability and supporting government taxation and welfare policies. Thus, the accuracy of tourism demand estimation has far-reaching impacts on the economy.

The effectiveness of demand modeling depends on the underlying economic theories used to explain and estimate it. Like many fields studying consumption behavior, tourism demand modeling is predominantly based on microeconomic demand theory from neoclassical economics. Econometric demand models have been widely used to estimate market demand and identify its correlations with key determinants. However, despite success at the aggregate level, the modeling of tourism demand at the disaggregate level is relatively unexplored. This thesis, leveraging behavioral economic demand models, develops an innovative conceptual framework to bridge the gap between aggregate and disaggregate demand modeling. It demonstrates the framework's feasibility and advantages through two empirical applications in tourism, revealing consumers' heterogeneous demand curves by personal characteristics and contextual factors.

This chapter presents an overview of the thesis. Section 1.1 outlines the research background. Section 1.2 discusses existing limitations in the literature and identifies research gaps. Section 1.3 articulates the research aim and objectives to address these problems. Section 1.4 explains the philosophical stances underpinning this thesis. Finally, Section 1.5 highlights the contributions of this thesis.

1.1 Research Background

Neoclassical economics forms the foundation of modern mainstream economics, emphasizing the two fundamental forces in market economies – supply and demand – as determinants of price and demand. It explains economic activities through these variables. Its branch, microeconomics, focuses on the decision-making processes of firms, households and individuals. The relationship between price or other determinants and demand is typically represented by a demand curve or model, with demand elasticity measuring both the direction and magnitude of the effects of these determinants on demand. While this framework advocates for the heterogeneity of demand curves among products, consumer-based differences in demand curves have not been well captured. The theorization of a market demand curve, formed by aggregating statistical-average individual demand curves, neglects variations across different individuals or consumer segments.

Based on microeconomic demand theory, tourism demand modeling has primarily focused on analyzing the effects of significant determinants and forecasting future demand (Song et al., 2009). This line of research can be traced back to the 1960s (Gerakis, 1965; Gray, 1966; Guthrie, 1961), with considerable advancements made since the 1990s, spurred by the introduction of advanced econometrics in tourism studies (Ashworth & Johnson, 1990; Crouch et al., 1992). Consequently, econometric demand models employed in tourism research have been aimed at market demand modeling, estimation, and forecasting using aggregate secondary data.

In contrast to neoclassical economics, which prioritizes theoretical generality over descriptive and predictive accuracy at the individual level, behavioral economics emphasizes the heterogeneity of demand and decision-making patterns across individuals and contexts. Behavioral economics effectively has two branches – “cognitive” behavioral economics and “behavioral” behavioral economics (Magoon & Hursh, 2011). “Cognitive” behavioral economics explores human cognitive biases in decision-making, challenging the assumption of perfect rationality and providing point estimates of behavior. In contrast, “behavioral” behavioral economics examines external influences (e.g., reinforcement, deterrence) on behavior and aims to establish functional relationships between them (i.e., behavioral economic demand models). Thus, while the behavioral branch shares a common research goal with econometric demand modeling in microeconomics, the two differ in their perspectives on data aggregation. Modeling aggregate demand provides broad economic implications but overlooks significant details about demand variations due to individual characteristics. This can compromise the accuracy of disaggregate-level estimations and the effectiveness of derived business and public strategies. In this context, “behavioral” behavioral economics presents a promising methodology to address the existing challenges in tourism demand modeling.

1.2 Problem Statement

Positioned at the pivotal intersection of neoclassical economics (specifically, the microeconomic demand theory) and “behavioral” behavioral economics, this thesis reviews and appraises the literature on microeconomic demand theory and the behavioral branch of behavioral economics, focusing on the concepts of the demand curve and demand model. It identifies and acknowledges research limitations and gaps within both theoretical frameworks.

1.2.1 Microeconomic demand theory

Microeconomic demand theory and demand curve analysis are rooted in the theory of consumer choice. This theory posits that consumers make optimal choices in each decision-making process based on their personal preferences and budget constraints, and these choices collectively form an individual demand curve (Rittenberg & Tregarthen, 2013). However, this theoretical foundation of microeconomics brings forth two main problems. Firstly, the assumption of perfect rationality, depicting individuals as Homo economicus who are consistently rational and capable of maximizing utility, is overly stringent and does not accurately reflect reality. Simon (1957, 1982) introduced the concept of bounded rationality, comparing it to a pair of scissors with one blade representing human cognitive limits and the other environmental factors (Gigerenzer & Selten, 2002). This highlights the impact of both internal consciousness (the focus of "cognitive" behavioral economics) and external conditions (the focus of "behavioral" behavioral economics) on decision-making. Specifically regarding external conditions, it has been empirically confirmed that tourists' demand patterns respond to various environmental factors, such as travel risks (Gray & Wilson, 2009; Li et al., 2021) and arrangements (Poon & Huang, 2017; Ye et al., 2023). Hence, it is reasonable to assume that a relevant environmental factor can shape individual decisions and, consequently, the entire demand curve. However, most tourism demand modeling studies have overlooked the potential shifts in consumers' demand curves and elasticities across different environments or situations, focusing only on temporary fluctuations in demand levels (He et al., 2022; Page et al., 2012).

The second problem is that, although the theory of consumer choice acknowledges the decisive role of personal preferences and budgets in shaping individual demand curves, most demand modeling practices have failed to describe the heterogeneity of demand curves among different consumers. Within the theoretical foundation for the empirical realization of a market demand curve, each consumer is viewed as a homogeneous entity representing the market average demand. The fitted market demand curve equals the individual demand curve of the statistical-average individual multiplied by the number of consumers in the market (Thomas, 1985). Even when quantifiable characteristics like income and age are included in models, they serve more as statistics of population distribution rather than indicators of distinct consumers, as the estimated coefficients explain changes in market demand given a unit change in the average income or age of all consumers in the market. Given that individual characteristics are closely related to tourists' preferences (Chen et al., 2019; Chou & Chen, 2014; Masiero et al., 2020) and consequently their demand curves, it is essential to model disaggregate demand curves by grouping tourists according to specific characteristic variables to systematically explore variations in demand curves and elasticities across different tourists.

Regarding the specific econometric demand models widely used in tourism and other economic contexts, two additional problems have been identified. Firstly, researchers have rarely focused on specifying the dynamics of elasticity along the demand curve, often estimating elasticity as a single constant. This preference can be attributed to two factors. On one hand, dynamic-elasticity demand models are less favored compared to their constant-elasticity counterparts (in a double-log functional form) due to the simplicity of model estimation and parameter interpretation in the latter. On the other hand, when employing dynamic-elasticity demand models, researchers typically calculate demand elasticity at the average price to derive a single constant, aiming to encompass more information in one indicator and simplify managerial understanding (Song et al., 2010; Song et al., 2009). Taking a step back, the popular time-varying parameter technique in tourism demand modeling captures the dynamics of elasticity over time rather than over the price range, and the derived elasticity coefficients are still average values of aggregate data within a limited price fluctuation space (Song, Li, et al., 2011). Nevertheless, a constant demand elasticity with price is rare and considered a theoretically special case of the demand curve, while economists generally believe that for most demand curves, elasticity increases with price (Perloff, 2018). Therefore, rather than estimating a constant elasticity coefficient, it is more accurate and comprehensive to specify the dynamics of elasticity with price using an appropriate parameter.

Secondly, traditional econometric demand modeling fails to delineate complete demand curves from zero price to a breakpoint price at which consumption ceases. The issue of incomplete demand curve modeling is primarily due to the lack of substantial price points in secondary tourism demand data, which most existing tourism demand modeling studies are based on (Song et al., 2009). This highlights the advantage of experiments where demand data at various price points (including extreme values like zero and very high prices) can be collected. From the perspective of behavioral science, a complete demand curve can reveal the full picture of a consumer's cost-benefit judgment and how it is shifted by environmental factors. From the perspective of economic science, fitting the complete demand curve and parameterizing the elasticity dynamics over the entire price range improve the goodness of fit (as elasticity is dynamic along most demand curves), locate the optimal pricing point where revenue is maximized, and predict the impacts of cost-related business strategies and policies on consumer demand (Hursh, 1980; Hursh & Roma, 2013). Therefore, mapping out a complete demand curve is essential for advancing demand modeling practice but requires a new data source that encompasses the full price range.

1.2.2 "Behavioral" behavioral economics

This thesis introduces "behavioral" behavioral economics to tourism demand modeling and demonstrates that its quantitative framework offers viable solutions to the aforementioned issues.

The theoretical underpinnings of "behavioral" behavioral economics are rooted in the intersection of operant psychology and microeconomic demand theory. This framework, initially developed by behavioral psychologists, measures the value of reinforcers, which are stimuli that influence behavior by increasing or decreasing its likelihood. In this context, economic goods are viewed as reinforcers, with price representing any effort or risk of loss (such as money, time, or energy) required to obtain the good. The demand curve in this framework delineates cost-benefit interactions, using parameters like demand intensity (baseline consumption when price is zero) and elasticity (rate of demand decay with increasing price). Elasticity in "behavioral" behavioral economics is dynamic, increasing with price and reflecting the good's essential value, which indicates its efficacy in reinforcing consumption despite rising costs. This approach contrasts with traditional microeconomic views that treat one single elasticity coefficient as the manifestation of the property of a good.

The behavioral economic demand framework overcomes the limitations of the microeconomic demand framework in two major aspects. Firstly, it is crucial that the fitted demand curve allows elasticity to change rather than estimating it as a constant regardless of cost conditions. While previous studies have used dynamic-elasticity demand models, they often estimate elasticity as a single constant, typically at the average price, due to the complexity of calculating it at each price point. The behavioral economic demand model addresses this by parameterizing the change in elasticity with price using a single parameter, thus enhancing both specification and interpretability. Consequently, the demand curve is depicted as a downward-sloping concave curve on logarithmic coordinates, indicating an increase in elasticity with price (Gilroy et al., 2021; Hursh & Silberberg, 2008; Koffarnus, Franck, et al., 2015). This model empirically realizes a new theoretical framework by measuring elasticity over a continuum and defining the nature of a good through elasticity dynamics, rather than through point elasticity.

Secondly, addressing the gap in fitting complete demand curves at the disaggregate level – necessary to uncover heterogeneous demand curves across customer groups and contexts – requires innovative data collection methods. This leads to the adoption of the hypothetical purchase task technique (Jacobs & Bickel, 1999), widely used in empirical studies within "behavioral" behavioral economics. By embedding it in an experimental design to simulate the consumption context, the hypothetical purchase task gathers individuals' demand data at various price points through questionnaires. The main difference between traditional econometric demand models and behavioral economic demand models lies in their focus; the former predominantly models time-series data to describe short-term or long-term trends, while the latter emphasizes modeling cross-sectional data where each subject's responses are crucial.

Despite the promising theoretical foundation offered by "behavioral" behavioral economics to address key issues in tourism demand modeling, notable research gaps remain in this field. First, applications of behavioral economic demand models have largely focused on studying addictive behaviors related to substances like alcohol, drugs and tobacco (González-Roz et al., 2019; Kaplan et al., 2018; Strickland et al., 2019). There is a significant lack of empirical studies in broader contexts, such as regular consumption, to strengthen its generalizability and superiority. Second, most demand studies based on behavioral economic demand models employ univariate models, designed to map demand curves onto a two-dimensional price-demand space. Typically, the own-price [cross-price] demand curve is fitted using a model where the own price [cross price] is the sole explanatory variable (Hursh & Roma, 2013). Although this approach is effective for constructing complete demand curves, integrating multiple key determinants into the model could enhance the precision of demand estimation, as is done in traditional econometric demand models. A multivariate behavioral economic demand model has been proposed to incorporate both own price and cross price (Hursh & Schwartz, 2023), but it has yet to be applied in fitting demand data or tested for validity.

1.3 Research Aim and Objectives

This thesis addresses the identified research gaps in both tourism and "behavioral" behavioral economics by being the first to introduce and apply behavioral economic demand models for modeling tourism demand. It uniquely considers individual differences and environmental factors and verifies the effectiveness of the newly developed multivariate behavioral economic demand model in estimating product consumption.

Accordingly, the overarching aim of this research is *to model demand data at the disaggregate level from a behavioral economics perspective, thereby exploring the influences of individual differences and environmental factors on consumers' complete demand curves for a specific tourism product*.

Following the research aim, four research objectives are proposed:

- To critically evaluate tourism demand modeling research and introduce "behavioral" behavioral economics and its methodology to address the challenges faced in traditional tourism demand modeling.
- To empirically demonstrate the advantages of disaggregate demand modeling by utilizing behavioral economic demand models to fit diverse demand curves across various customer groups and contexts.
- To enhance the fitting of demand curves by employing the multivariate behavioral economic demand model, aiming to comprehensively describe the product's competition with its primary substitute in view of customer groups and consumption situations.
- To provide policy and business operation recommendations based on the empirical analysis derived from the demand models.

Considering that tourism comprises various sectors such as lodging, transportation, food and beverage, and tourist attractions, each with its own relatively independent and integrated market, economic activities within these sectors are likely to differ significantly, especially at the disaggregate level. Therefore, rather than estimating a general demand curve for an entire tourism destination, the empirical part of this thesis, exemplifying the novel methodology, focuses specifically on the lodging sector. It conducts in-depth analyses of hotel demand curves and the substitutive relationship between hotels and sharing accommodation.

1.4 Research Philosophy and Methodology

The research aim serves as the core foundation of a study, determining its philosophical stance and the research paradigm to be adopted. Scientific research can be classified into three fundamental types based on different research aims: pure research, which aims to produce or extend knowledge by discovering relationships between variables; applied research, which demonstrates the practical applicability of knowledge; and evaluation research, which assesses the outcomes of applying theoretical frameworks for problem-solving (Easterby-Smith et al., 2018; Miller & Salkind, 2002). These three types collectively embody the integral process of knowledge translation, encompassing the creation, application and evaluation of knowledge (Thorpe et al., 2011).

Determining whether a research work belongs to pure research or applied research can be influenced by the perspective from which the research is viewed – whether within a specific field or in the context of broader scientific development. This thesis is considered pure research within the tourism field because it aims to expand knowledge in this domain. Specifically, the primary goal of this thesis is to gain new knowledge and understanding of the heterogeneity of demand curves at the disaggregate level, which has not been systematically explored or quantified before in both tourism and mainstream microeconomic studies. The research intends to demonstrate a novel methodology and adapt it to the tourism context to establish a conceptual framework with empirical verification. It focuses on fundamental concepts and theories while demonstrating the application of the proposed approach. Future applications can be as specific as constructing the demand curves for particular customer segments or even individual businesses. This categorization fundamentally shapes the research philosophy of the thesis.

1.4.1 Research philosophy

Research philosophy pertains to the assumptions or stances that researchers hold about the creation of knowledge, specifically concerning the relationship between data and theory. It underpins the research design, guiding the process of deriving results and conclusions from empirical studies (J. W. Creswell & J. D. Creswell, 2023). A clear understanding of these philosophical foundations is crucial for positioning the researcher's role in research activities, elucidating the research design, assessing the feasibility of the research, and facilitating innovative research practices (Saunders et al., 2019). If we liken the entire research process to a tree, then the research philosophy can be viewed as the trunk, supporting the growth of leaves (data collection and analysis) and fruit (research output), as suggested by Easterby-Smith et al. (2018). At the core of this trunk is *ontology*, representing philosophical beliefs about the nature of reality and forming the foundation of the research tradition, akin to the tree's roots. Surrounding this is *epistemology*, which involves views on how to investigate the nature of reality. The next layer is *methodology*, encompassing the organization of specific methods and techniques to inquire into a question. As a result, the outermost layer of the trunk symbolizes the research methods used for data collection and analysis. This section will unravel the research philosophy and the formation of the research paradigm in this thesis.

1.4.1.1 Ontology

Different ontological stances exist along a continuum, with two extremes representing opposing views on reality: *realism* and *nominalism*. Realism posits that the world and reality exist independently of observation, advocating for a single, discoverable truth for any given question (Blaikie, 2007). In contrast, nominalism contends that reality is subjective, existing solely within people's perceptions, thus denying an objective truth and asserting that facts are human constructs (Cunliffe, 2001). Between these extremes lie positions such as *internal realism* and *relativism*. Internal realism, a moderated form of realism, maintains that while reality is objective and there is a singular truth, it cannot be directly observed or acquired due to the subjective nature of human understanding (Putnam, 1987). Relativism, on the other hand, suggests the existence of multiple truths, as reality and facts vary based on researchers' perspectives and the contexts of their research (Collins, 1983).

In this thesis, the stance is that the world and reality are objective, and an absolute truth exists, specifically concerning the relationship between demand curves and their influencing factors. However, given the social science nature of this research, which involves extensive human activities, reality cannot be fully observed or objectively assessed. The researcher can only approach reality indirectly, making necessary assumptions (e.g., ceteris paribus) and using proxies to measure otherwise inaccessible variables (e.g., established measures for psychological factors). Therefore, the ontological position adopted in this thesis aligns with internal realism.

1.4.1.2 Epistemology

Epistemological positions can also be placed on a continuum between two opposing beliefs: *positivism* and *constructionism*. Positivism, rooted in realism and internal realism, acknowledges an objective reality and truth. It implies that reality should be observed, measured and assessed through objective methods that disregard personal biases, with researchers acting as detached observers. The positivist research process typically involves hypothesis testing and describing causality. In contrast, constructionism, deriving from relativism and nominalism, assumes a subjective reality shaped by people's perceptions and experiences. This view emphasizes the significant role of individual perspectives and experiences in the development of science, positioning researchers as integral parts of the research (Brotherton, 2015; Easterby-Smith et al., 2018). *Pragmatism*, which lies between these extremes, advocates that reality should be understood through practical approaches, utilizing both objective and subjective methods. Research under this epistemological stance often employs mixed methods (Gill et al., 2010).

In alignment with the thesis's foundation of internal realism, an epistemological position of positivism is adopted. This approach aims to objectively measure and describe the social world, using methods such as surveys with quantifiable questions and demand modeling techniques. The focus is on explaining the causality and quantitative relationships among external factors, particularly examining the heterogeneity of demand curves across different consumers and contexts.

1.4.1.3 Methodology

Methodology, as the final element in the logical chain of research philosophy, determines the research paradigm, building upon the foundations of ontology and epistemology. The chosen ontological and epistemological stances significantly influence the selection of methodology, research design and the eventual application of research methods and techniques (Neuman, 2011). This thesis identifies itself as quantitative research, aiming to objectively uncover the effects of individual differences and contextual variables on demand curves. It upholds the philosophical position of internal realism in ontology and positivism in epistemology. Recognizing that economic variables at the individual level (i.e., facts) cannot be directly observed in their natural state, it becomes necessary to deduce potential principles and theories through regression analysis of large-sample survey data. Consequently, this thesis adopts a deductive research approach, starting with propositions based on "behavioral" behavioral economics and mainstream economics to test and expand existing theories.

With the research paradigm clearly defined, a concrete research design can now be developed. This thesis comprises three studies, each progressively contributing to the achievement of the overall research aim and objectives. Section 1.4.2 will detail the methodological designs of these three studies.

1.4.2 Thesis structure

This thesis adopts a manuscript format to present its three studies. The specific research purposes, research designs and research methods for each study are summarized as follows:

The first study, detailed in Chapter 2, offers a critical reflection on four prevailing issues in tourism demand modeling, specifically in the context of microeconomic demand theory and econometric demand models, as identified in existing literature. To address these issues, the study introduces and adapts "behavioral" behavioral economics to develop a new analytical framework. This framework, grounded in both theoretical concepts and mathematical functions, facilitates tourism demand modeling at the disaggregate level, incorporating individual differences and environmental factors. It also suggests directions for future empirical applications. This study has been published in the *International Journal of Contemporary Hospitality Management*.

The second study, featured in Chapter 3, acts as an empirical application of the analytical framework developed in the first study. It investigates the heterogeneity of hotel demand curves across different consumer demographics and contexts. The study employs a between-subjects experimental design using randomly assigned hypothetical purchase tasks, with a 3 (*hotel type*: economy, midscale and upscale) × 2 (*consumption situation*: normal and pandemic) setup. By constructing disaggregate demand curves for the three hotel types using a behavioral economic demand model, this study reveals how demand curves vary among consumers based on gender, age, income, preference and risk tolerance, and examines the impact of a pandemic on these curves. The model results, tailored to specific market segments, enable the provision of detailed managerial recommendations for customer and crisis management for each hotel type. This study is in preparation for submission to the *Journal of Hospitality and Tourism Research*.

The third study, presented in Chapter 4, delves deeper into the use of behavioral economic demand models to analyze product interactions, focusing particularly on the substitution between sharing accommodation and hotels. Employing a between-subjects experimental design, the study utilizes a 3 (*hotel type*: economy, midscale and upscale) × 2 (*travel companions*: traveling alone and traveling with friends) configuration, collecting data through randomly assigned hypothetical purchase tasks. It applies the alone-price demand model, the multivariate own-price demand model, and the cross-price demand model from behavioral economics. This approach enables the construction of alone-price and own-price demand curves for the three hotel types, as well as the cross-price demand curves for sharing accommodation in relation to hotel pricing. The study quantifies the dual-directional substitutive relationship between sharing accommodation and various hotel types and examines the variations in substitutability among consumers based on gender, age and preference, and between different travel companion scenarios. The research provides new insights into the substitution dynamics between sharing accommodation and hotels across diverse contexts. This study has been published in the *Annals of Tourism Research*.

Unified by the overarching theme of disaggregate demand modeling, the three studies in this thesis progressively introduce and develop the application framework of "behavioral" behavioral economics in tourism demand modeling. While they collectively advance this central theme, each study is also relatively independent, addressing specific research questions and yielding unique theoretical and practical implications.

1.4.3 Research ethics

This section outlines the ethical considerations and principles adhered to throughout the research process. These ethical considerations are fundamental to the integrity and credibility of the research findings. The data collection process was initiated after obtaining human subjects ethics approval from The Hong Kong Polytechnic University (application no.: HSEARS20211207001).

The design of the questionnaires employed in this research prioritizes the well-being and dignity of participants. Particular care has been taken to ensure that the questions posed are harmless and do not cause any undue distress. The intent is to gather information while respecting the participants' emotional and psychological well-being. The data collection process has been executed in collaboration with qualified online research firms, which are equipped to guarantee the privacy of participants throughout the data collection phase. All participants involved in this study are adults, ensuring their legal capacity to consent. Participants have been recruited on a voluntary basis, with informed consent obtained before their inclusion in the study. The consent process has included clear communication of the research topics and procedures, allowing participants to make an informed decision to participate. A strict policy of anonymity has implemented to ensure that all recruited participants, as well as their relatives and associated organizations (if applicable), remain unidentified in any published or disseminated material arising from this research. After the completion of data collection, comprehensive measures have been undertaken to maintain the confidentiality of the gathered information. Access to raw data is restricted to authorized personnel only, and any data storage or transfer adheres to the highest standards of security.

1.5 Thesis Contributions

This thesis significantly advances the theoretical development of consumer demand modeling in the realms of “behavioral” behavioral economics and tourism research. From a behavioral economics perspective, it extends the application of behavioral economic demand models beyond addiction studies to broader economic contexts, confirming their validity and advantages in estimating leisure consumption through empirical research. Notably, this thesis pioneers the use of the multivariate behavioral economic demand model to fit demand data and quantify the substitutive relationship between two related tourism products, paving the way for future research in methodological applications for substitution and complementation analyses.

In the field of tourism research, this thesis marks the inaugural integration of “behavioral” behavioral economics and its demand curve analysis into tourism demand modeling, challenging the limitations of traditional econometric demand models. It explores the heterogeneity of demand curves across different consumers and contexts, thereby advancing tourism demand modeling from an aggregate to a disaggregate level. This novel approach addresses research gaps in capturing the dynamics of elasticity along complete demand curves, leading to more comprehensive and realistic demand curve construction.

Practically, the thesis enhances the effectiveness of business strategies in the lodging sector. The findings inform pricing strategies for various hotel types by identifying the optimal pricing points for maximizing total revenue, including adjustments based on customer groups and travel situations. The in-depth analysis of individual differences and environmental factors on hotel demand curves offers businesses deeper insights into their target customers’ profiles and supports the development of more customized marketing strategies under specific market conditions. Additionally, the detailed examination of the substitutive relationship between sharing accommodation and different hotel types clarifies the state of market competition, guiding strategies to retain or attract customers from competitors. Lastly, the overall methodology’s flexibility allows individual businesses to construct their own demand curves based on customer composition, yielding more precise and informative results for the development of specific business strategies.

Chapter 2 A Behavioral Economics Approach to Hospitality and Tourism Research

This chapter introduces the first study of this thesis, which is a conceptual paper published in the *International Journal of Contemporary Hospitality Management* (Song & Lin, 2023). Section 2.1 outlines the research motivations. Section 2.2 identifies four major issues in tourism demand modeling. Section 2.3 explains the two branches of behavioral economics, focusing on the introduction of "behavioral" behavioral economics and its methodologies for demand modeling. Section 2.4 develops a new conceptual model by integrating "behavioral" behavioral economics into tourism research, aiming to address the identified issues and facilitate demand modeling at the disaggregate level. Section 2.5 concludes the chapter with a discussion of the research implications and directions for future empirical studies.

2.0 Abstract

Purpose – This study aims to critically evaluate hospitality and tourism demand research and introduce a behavioral economics approach to solve the problems faced by researchers.

Design/methodology/approach – Current issues in hospitality and tourism demand analysis are identified through critical reflection, and a behavioral economics approach is adopted to develop a new conceptual framework.

Findings – Four issues in hospitality and tourism studies are identified from the microeconomic theory and econometric modeling perspectives. The study's demand framework provides both a theoretical underpinning and quantitative models to resolve the identified issues. With a focus on consumers' cost–benefit assessments in light of individual differences and environmental factors, the authors' conceptual framework represents a new effort to quantify hospitality and tourism demand at the disaggregate level with interactive multiple demand curve estimations.

Research limitations/implications – The study's analytical framework for hospitality and tourism demand analysis is unique, and it fills the research gap. However, this research is still in the conceptual stage, and the authors leave it to future studies to empirically test the framework.

Practical implications – The proposed demand framework at the disaggregate level will benefit both private and public sectors involved in hospitality and tourism businesses in terms of pricing, marketing and policymaking.

Originality/value – The authors offer a new conceptual model that bridges the gap between aggregate and disaggregate hospitality and tourism demand analyses. Specifically, the authors identify research directions for future hospitality and tourism demand research involving individual tourists/consumers at the disaggregate level.

2.1 Introduction

With the remarkable improvement in living standards over the years, the consumption of hospitality and tourism products/services has become an increasingly important component in consumers' expenditure budgets, improving their well-being and generating positive externalities. As a labor-intensive industry, hospitality and tourism encompasses copious economic activities across various business sectors in which the demand for hospitality and tourism products/services plays a critical role in determining corporate profitability and informing government taxation and welfare policies. Therefore, analyzing the determinants of hospitality and tourism demand and accurately estimating that demand present considerable challenges to academics and practitioners alike.

Recent hospitality and tourism demand studies are rooted in the neoclassical demand theory, which analyzes the effects of demand determinants on magnitude and direction. Estimated demand functions are then used to forecast future demand. With the introduction of advanced econometric methods, hospitality and tourism demand analysis now emphasizes modeling techniques that use aggregated secondary data related to international and regional hotel guests/tourists (Song et al., 2009). Despite the success of these modeling techniques at the aggregate level, they make a series of strict assumptions about consumers, and for that reason, they neglect a considerable amount of information relating to individual differences and environmental factors.

Unlike neoclassical economics, which sacrifices descriptive power at the individual level for theoretical generality and predictability, behavioral economics is based on the theory of bounded rationality, stressing the inconsistency of behavioral patterns and decisions across individual consumers and contexts (Simon, 1956, 1982). Although hospitality and tourism researchers are increasingly aware of behavioral heterogeneity at the micro level, applications of behavioral economics to hospitality and tourism research are limited to ad hoc estimates of demand functions at the individual consumer level, which are difficult to generalize. Furthermore, the behavioral heterogeneity derived from analyzing individual demand behavior has yet to be properly integrated into a systematic econometric modeling process to enable demand analysis to be conducted within an acceptable framework.

We believe that future hospitality and tourism demand research will urgently need to find a balance between the above-referenced schools of thought. In that regard, in this reflection paper, we critically evaluate hospitality and tourism demand studies and introduce a behavioral economic research framework as a viable solution to researchers' problems. This framework also suggests possible future research directions in hospitality and tourism demand analysis.

2.2 Current Issues in Hospitality and Tourism Demand Analysis

Standing at the critical point between neoclassical economics and behavioral economics, we recognize that the reason for the most significant issues restraining the further advancement of hospitality and tourism demand analysis is that the microeconomic demand theory is the theoretical foundation of econometric estimates of demand. Four significant issues are discussed in the following sections.

2.2.1 Theoretical foundation

As the theoretical foundation of hospitality and tourism demand analysis, the microeconomic demand theory explains an individual's decision-making process toward a final consumption decision based on the assumption that the consumer is a utility maximizer who pursues the optimal choice subject to personal preference and budget constraints. This argument leads to two major problems, which naturally have been inherited by the derived studies on demand.

Problem 1. The assumption of a rational consumer is too restrictive. The postulation of consumer choice optimization originates from the rational choice theory, which assumes that individual consumers are perfectly rational in their cost-benefit analyses for decision-making. More specifically, individuals are expected to be consistently rational regardless of context and to have adequate information and ability to seek utility maximization (Gilboa, 2010). However, this ideal is far from reality even when consumer behavior is examined at the macro level. The notion of perfect rationality has been disputed in the general field of economics ever since the proposition of bounded rationality, which contends that people are "satisficers" rather than utility maximizers (Simon, 1982). Empirical studies in broader research areas have also proven that consumers' decisions are context-dependent and susceptible to multifarious environmental factors, such as risk (Kahneman & Tversky, 1979), framing (Tversky & Kahneman, 1981) and choice architecture (Thaler & Sunstein, 2008). There have been similar findings in hospitality and tourism studies, which have discovered that tourists' or hotel/restaurant guests' preferences and decisions are altered by crowding (Hou et al., 2021), information framing (Denizci Guillet et al., 2022), travel hazards especially COVID-19 (Li et al., 2021) and word of mouth (Song et al., 2022). These results imply that the demand for hospitality and tourism products/services is sensitized to specific consumption contexts. However, this behavioral deviation from perfect rationality, especially in terms of the contextual dependence of demand, has attracted less attention from researchers whose work in hospitality and tourism demand studies is based on the microeconomic demand theory.

Problem 2. Individual differences are theoretically emphasized but practically ignored. Although the theory of consumer choice asserts that an individual's consumption decision is subject to personal preferences and budget constraints, theory-implied individual differences have not been well captured in existing demand modeling processes because of the research concentration on market demand estimation and data unavailability at the individual level (Song et al., 2009). Moreover, because the theory of consumer choice provides a theoretical underpinning to individual demand instead of market demand, the microeconomic theory rationalizes market demand as the direct summation of individual demand by devising a "representative consumer" who stands for the statistical average of the market (Thomas, 1985). In other words, the modeling of market demand considers all individuals identically as representative consumers, and individual demands are therefore averaged out to arrival at market demand. This treatment is undoubtedly insufficient to integrate the heterogeneity of preferences caused by individual differences in sociodemographics (Bogicevic et al., 2018), personalities (Poon & Huang, 2017) and past experiences (Masiero & Qiu, 2018). Individuals with disparate personal preferences, even if sharing the same budget, make different purchase decisions, which consequently lead to different demand curves. Thus, modeling the demand of a "representative consumer" flattens the variations in demand patterns across all kinds of consumers.

In summary, the strict assumptions in theory and the stress on market demand in practice tacitly acknowledge the high homogeneity of individuals' consumption behaviors while disregarding behavioral heterogeneity in light of individual differences and environmental factors. These two problems are also embedded in applications of econometric demand models in hospitality and tourism research.

2.2.2 Econometric demand modeling

Two further problems have been recognized with respect to the econometric demand models used in hospitality and tourism demand analysis. We explain these problems based on the demand curve, which illustrates the relationship between the price of a hospitality and tourism product and the quantity demanded.

Problem 3. The dynamics of elasticity along the demand curve are not parameterized. The linear demand curves on logarithmic coordinates, commonly seen in hospitality and tourism demand modeling studies, require an exactly constant price elasticity of demand over the price range, and we categorize the models fitting these demand curves as "constant-elasticity demand models" (in double-log functional form). However, they are rarely observed in the real economy, given that consumers are not perfectly rational in their consumption decisions. A more realistic assumption would be that elasticity varies with price. In this case, the demand model is referred to as a "dynamic-elasticity demand model" (in linear/semi-log functional form). However, researchers have rarely focused on parameterizing elasticity dynamics along the demand curve but instead have become habituated to specifying elasticity as a constant measure of the demand response to price change. One of the reasons that constant-elasticity demand models are preferred to their dynamic-elasticity counterparts is because it is easy to estimate the model and interpret the parameters (Song et al., 2009). Furthermore, for reasons of statistical convenience, even when dynamic-elasticity demand models are applied, elasticity is commonly estimated as an average constant indicator. In effect, researchers have paid the most attention to the dynamics of elasticity over time (time-varying elasticity) instead of price or other cost variables. One important exception in this respect is the use of time-varying parameter models in tourism demand analysis to relax the constancy of elasticity over the sample period (Song, Li, et al., 2011). Peng et al. (2015) found that income elasticity tends to increase over time, and Smeral and Song (2015) as well as Smeral (2019) concluded that income elasticity fluctuates across business cycles, whereas the price elasticity tends to remain unaffected. This shows that the price elasiticity is special, in that it can reveal a habitual pattern of consumer behavior that is relatively stable over time. Therefore, it is inappropriate in demand analysis to specify only the dynamics of price elasticity over time without probing its evolution along the demand curve, especially when attempting to understand consumers' decision-making in the cost-benefit analysis.

Problem 4. Current demand modeling exercises do not map out complete demand curves. The estimated econometric demand models have largely relied on historical data from secondary sources. Survey data are occasionally used particularly for modeling household or organization demand, but the surveys are generally implemented with non-experimental designs (Song et al., 2009). Both methods of data collection do not necessarily reflect substantial price fluctuations, preventing researchers from fully examining consumers' responses to a wide range of price changes. This restricts our understanding of the complete shape of a demand curve, especially the variation of demand over the full price range – from a free product/service, which attracts a maximum level of demand, to a price that is high enough to stop consumers from purchasing. As a result, a linkage among price, demand and business revenue (or consumer expenditure) cannot be established, hindering practitioners from considering important implications that can help them formulate optimal pricing strategies (e.g., price adjustment) or public policies (e.g., taxes and rebates) to manipulate demand. Therefore, the demand curve over the full price range must be constructed to exhibit its complete shape and reveal consumers' dynamic cost-benefit judgments. This means that secondary data are insufficient to explore consumer demand from a behavioral perspective.

These critical microeconomic demand theory issues in hospitality and tourism demand studies must be resolved, and therefore, a novel conceptual framework must be developed. This framework should both relax the strict and unrealistic assumptions about economic agents and refocus the quantitative analysis of demand from the aggregate level to the disaggregate level.

More specifically, the framework requires a proper demand model with one additional parameter that specifies the dynamics of elasticity over the full price range for the sake of modeling thoroughness and interpretability. Furthermore, this framework requires a new data collection method to ensure that individual demand data in a variety of decision-making contexts are attainable. In the next section, we introduce the behavioral economics approach and argue that it offers a unified conceptual and quantitative framework to help resolve these problems.

2.3 Behavioral Economics Theory

2.3.1 Two branches of behavioral economics

Taking bounded rationality as its core, behavioral economics holds that people are not consistently rational; restricted by their own biases; subject to external conditions; and sometimes altruistic and fairness oriented. Simon (1956) likened bounded rationality to a pair of scissors, with one blade representing human cognitive limits and the other blade representing environmental structures, underscoring the influential power of both the internal consciousness and external contextual factors to shape decision-making. Correspondingly, two branches of behavioral economics are derived from the two sides of bounded rationality (Table 2.1).

Table 2.1 Two branches of behavioral economics.

Features	"Cognitive" behavioral economics	"Behavioral" behavioral economics
Origin	Cognitive psychology into microeconomics	Microeconomics into operant psychology
Essence	Behavior of economics	Economics of behavior
Preoccupation	Cognitive biases in decision-making	Environmental influences on behavior
Theoretical framework	Point estimates	Functional relationships
Logic of inquiry	Deductive	Inductive

Source: Adapted from Magoon and Hursh (2011).

Arising out of the introduction of cognitive psychology to microeconomics, "cognitive" behavioral economics concerns "psychological economics", and for that reason, it is also known as the "behavior of economics". As cognitive psychology pays special attention to the mental process, behavioral economics from this perspective uses the deductive approach to determine how cognitive biases cause people to diverge from rational decisions. Two of the most prominent theories emerging from this perspective are the prospect theory (Kahneman & Tversky, 1979) and nudge theory (Thaler & Sunstein, 2008). Nonetheless, some have charged that "cognitive" behavioral economics has insufficient generalizability to establish solid economic theories or axioms. This may be primarily attributed to its significant emphasis on point estimates of individual behavior, whose deviation from the general theory is normally discrete, contingent and unsystematic, making it difficult to theorize.

"Behavioral" behavioral economics introduces microeconomics into operant psychology (also known as "radical behaviorism", a subdiscipline of behavioral psychology). Referred to as the "economics of behavior", this branch concerns "economic psychology". Behavioral economics seeks to explore robust functional relationships between environmental factors and behavior through the inductive approach. Its advantage is its ability to find that ostensibly "irrational" behavior is instead orderly and systematic and fits well within a unified framework called the "behavioral economic demand framework", which contributes to the theorization and quantification of behavioral economics.

"Cognitive" behavioral economics exclusively dominates the empirical applications of hospitality and tourism demand studies. Many important principles of this branch of behavioral economics have been adapted to explore the decision-making of tourists, marketers and residents, including anchoring, the endowment effect and the framing effect (Lucas & Nemati, 2020; Tanford et al., 2019). In contrast to the popularity of "cognitive" behavioral economics, the application of "behavioral" behavioral economics in various research domains remains in its infancy. No attempt has been made to apply it in hospitality and tourism research. Nevertheless, we believe that "behavioral" behavioral economics creates a sound theoretical basis for resolving current issues and redirecting hospitality and tourism demand analysis. First, behavioral economics essentially attaches importance to human behavior and decision-making in view of individual differences and environmental factors. Second, demand modeling requires the establishment of a continuous functional relationship between demand and its determinants. As "cognitive" behavioral economics conducts point estimation, it is relatively less useful for demand modeling and the construction of a comprehensive quantitative framework. Fortunately, this can be achieved by the behavioral economic demand framework under "behavioral" behavioral economics.

2.3.2 Behavioral economic demand framework

2.3.2.1 Origin

Before merging with microeconomics, operant psychology concentrated on the environmental factors that act as stimuli and serve as the instant cause and chronic shaper of behavior. A stimulus performs as either a reinforcer whose presence increases the likelihood of a certain behavior or a punisher whose presence decreases the likelihood of that behavior. The emergence of the behavioral economic demand framework is motivated by behaviorists' endeavors to measure reinforcer value, i.e., a reinforcer's efficacy in influencing behavior. Its measurement metric evolved through several phases, until recent research introduced the microeconomic demand theory and indexed reinforcer value to demand (Hursh & Silberberg, 2008).

The most crucial analogy between microeconomics and operant psychology is that economic goods can be viewed as reinforcers. Consumers should behave as supposed (i.e., they should pay the required costs) to obtain the goods, and the presence of the goods performs as a stimulus to evoke and sustain this consumption behavior. As a corollary, the meanings of price and demand are extended in the operant paradigm. Any effort required and any risk of loss (e.g., money, time and energy) to obtain the reinforcer is a type of price, and the acquisition of any valued thing that acts as a reinforcer (e.g., physical commodity, experience and relationship) reflects demand (Hursh & Roma, 2013).

2.3.2.2 Demand curve, elasticity and essential value

The behavioral economic demand framework is based on a demand curve that delineates cost-benefit interactions across individuals and contexts. Two fundamental parameters are used to map a complete demand curve. To dictate the starting point of the demand curve, demand intensity (also called "baseline consumption") Q_0 is set to equal the demand level when the price is zero; the slope (i.e., elasticity) dictates the rate of decay. Apart from these, the breakpoint *BP* represents the price at which an individual ceases consumption. Through laboratory experiments, behavioral economists conclude that the demand curve on logarithmic coordinates is normally downward sloping with an accelerating speed of decrease, as exemplified in Figure 2.1. Put another way, a typical behavioral economic demand curve displays a progressively increasing elasticity with price, which implies an inverted U-shaped total revenue curve (called the "total output curve" in the operant paradigm). The price at which the output reaches the peak (O_{max}) is denoted as P_{max}, which is the optimal pricing point at which elasticity equals unity in absolute terms.

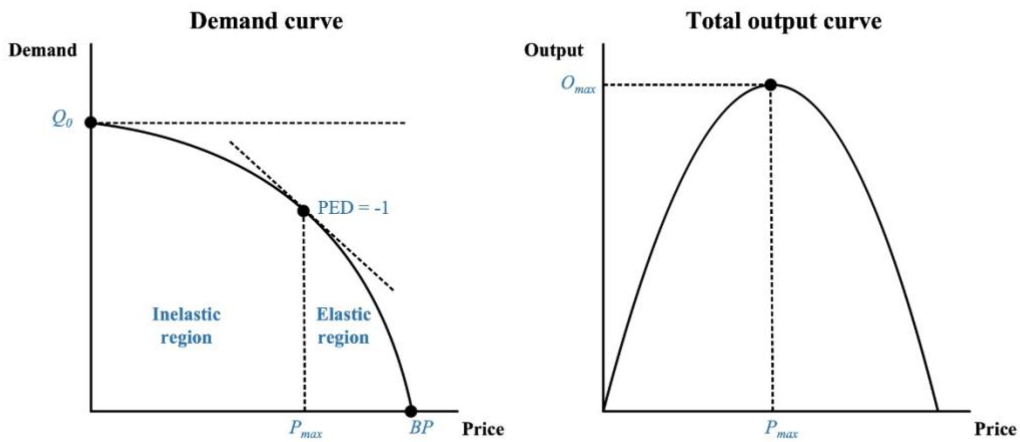


Figure 2.1 Typical behavioral economic demand curve and total output curve.

Within this framework, elasticity is imbued with new attributes and meanings. Behavioral economists review elasticity as a continuum, indicating that the elasticity of any good, regardless of its nature, eventually becomes elastic [inelastic] provided that the price increases [decreases] sufficiently. This contradicts the microeconomic argument that elasticity is an inherent property of goods; instead, the entire dynamic of elasticity is the property of the goods. Elasticity distinguishes goods by manifesting their efficacies in reinforcing consumption behavior, a concept termed "essential value". The more resistant to change the demand is with a price increase, the higher the value of the goods as a reinforcer in strengthening/maintaining consumption behavior, which indicates a higher essential value, and vice versa.

2.3.2.3 Behavioral economic demand models

The evolution of behavioral economic demand models involves the pursuit of finding a single parameter to properly specify the rate of change in elasticity and frame an increasingly negative slope for the demand curve on logarithmic coordinates. All of the models are capable of processing both individual and aggregate demand data. Three key models are introduced below.

Model 1. Exponential demand model

The exponential demand model proposed by Hursh and Silberberg (2008) presents a functional form with a single parameter to determine the change rate of elasticity with an exponential decay demand function of price:

$$logQ = logQ_0 + k(e^{-\alpha Q_0 P} - 1), \quad (2.1)$$

where k is the span parameter specifying the log range of the observed demand considering there is no lower bound on the log scale, and α is the parameter to be estimated, which stipulates the rate of decrease of the demand curve. A lower [higher] α indicates that the increasing rate of elasticity over the full price range is relatively slow [fast], meaning that consumer demand for the commodity is more [less] resistant to changes in price. In this case, the essential value of the commodity for this consumer is high [low]. Thus, there is an inverse relationship between essential value and α, but α is not a direct index of essential value, as the dynamic of elasticity is jointly determined by α and k. Therefore, it is preferable to quantify essential value using Equation 2.2 (Hursh, 2014) to obviate the effect of k and make essential value (*EV*) comparable across studies involving different span values.

$$EV = \frac{1}{100\alpha k^{1.5}} \quad (2.2)$$

Model 2. Exponentiated demand model

The exponential demand model has one general complication when it is fitted to the data on the log scale: the zero value is undefined. However, zero consumption values are exceptionally common in the application of behavioral economic demand models given that the full price range is accounted for, making the treatment of zero values quite influential in parameter estimation. To resolve this complication, Koffarnus, Franck, et al. (2015) offered the exponentiated demand model, which is simply the exponentiated form of the exponential demand model in which the data are fitted on the natural scale (Equation 2.3):

$$Q = Q_0 10^{k(e^{-\alpha Q_0 P} - 1)}. \quad (2.3)$$

As the exponential and exponentiated demand models are essentially identical, their parameters are comparable on the same scale. The most notable advantage of the exponentiated demand model is that original data can be directly accounted for without replacing zero values of consumption, and thus, they do not disturb the demand curve fitting.

Model 3. Zero-bounded demand model

The log scale is not only undefined at zero but also unbounded from below, which is why the exponential demand model includes parameter k to specify the span of $logQ$. However, the assignment of a k value is challenging because the span of individual demand data may vary so dramatically that it is difficult to apply a single k to represent all of the individual data series equally well. In addition, the existence of k prevents α from being a direct standardized index of essential value. The exponentiated demand model, as a variant of the exponential demand model, inherits this problem. Accordingly, the zero-bounded demand model was recently proposed by Gilroy et al. (2021) to settle those issues by replacing the log transformation with the inverse hyperbolic sine (IHS) transformation into the exponential demand model. This transformation can simulate logarithmic properties and accommodate zero/negative values. The $\log_{10}$-like transformation is calculated as follows:

$$IHS(x) = log\left(0.5x + \sqrt{0.25x^2 + 1}\right). \tag{2.4}$$

As $IHS(x)$ has a lower bound of zero, the span of demand data on the IHS scale simply equals $IHS(Q_0)$. The zero-bounded demand model is established by plugging the transformed demand into the exponential demand model according to Equation 2.4 and normalizing the α parameter to the span, written as follows:

$$IHS(Q) = IHS(Q_0)e^{-\frac{\alpha}{IHS(Q_0)}Q_0P}. \tag{2.5}$$

The zero-bounded demand model successfully resolves the complications of undefined zero value and lower bound on the log scale while maintaining the original functional form and parameter interpretations. Furthermore, it no longer needs an additional span parameter and is therefore simplified. The model is superior in terms of accommodating zero values on model fitting, but there is always a deviation, as the IHS scale cannot completely emulate the log scale. In this respect, the zero-bounded demand model is expected to be more adequate and robust when zero values are a serious concern; otherwise, the exponential and exponentiated demand models might be better choices. Given the recognition of both advantages and limitations for all three models, one should not conclude that any model consistently outperforms the others, and it is always imperative to conduct an empirical analysis to evaluate and select the model that performs better in describing a particular data set.

2.3.2.4 Hypothetical purchase task

As secondary demand data usually contain deficient price points for depicting a complete demand curve and provide fewer details about each individual consumer, behavioral economists have increasingly used hypothetical purchase task questionnaires to collect participants' intentional demand data. Research on hospitality and tourism demand is in a similar situation: the lack of demand modeling at the disaggregate level is rooted in data unavailability. Therefore, we introduce hypothetical purchase task as a novel method of data collection.

hypothetical purchase task implies an experimental design. It asks participants to indicate their demand at various predetermined prices in a hypothetical consumption scenario. Accordingly, treatment is exerted on participants through the description of a consumption scenario at the beginning of the hypothetical purchase task questionnaire, and the controlled variable is typically the demographics across treatment groups. Although it measures stated rather than actual consumption behavior, hypothetical purchase task has irreplaceable advantages and is probably the best alternative when secondary data are deficient. Moreover, effective techniques have been incorporated into the data-cleaning process to handle non-systematic hypothetical purchase task data and control hypothetical biases (Stein et al., 2015).

The generalizability of hypothetical purchase task to various generic goods was corroborated by the seminal writing of Roma et al. (2016), which is regarded as instructional in applying hypothetical purchase task in a wide range of disciplines. They tested the manipulations of two design factors – price density (i.e., the number of price levels at which participants are required to declare their demand) and purchase type (i.e., quantity demanded vs. purchase likelihood) – on the estimation performance of the exponential demand model for six goods differing in kind and price (i.e., hamburger/sandwich, toilet paper, pay-per-view movie/show/event, fine-dining restaurant meal, refrigerator and vacation package) and gave recommendations for the future use of hypothetical purchase task by researchers in various fields. In brief, a density of no less than nine prices is suggested, and both purchase types are verified as effective measures of demand.

2.3.2.5 Significance

The behavioral economic demand framework offers microeconomists a new lens through which to examine and apply demand theory. This pioneering framework of interpreting and parameterizing the dynamics of elasticity over the full price range produces a value metric that concentrates more closely on individual behavioral practices and their variations across each other. This is accomplished by stressing the cost-benefit interaction revealed from an individual's series of decisions. Furthermore, the definitions of price and demand are broadened, allowing for analyses of varying types of behavior (other than physical consumption) against physical costs, provided that the variables are quantifiable. This is particularly rewarding for hospitality and tourism demand studies that explore complex decision-making processes. In addition, the successful construction of individual demand curves opens the door to more systematic explorations of both the subjective and the objective factors that alter the demand curves for different groups, markets and populations.

2.4 New Conceptual Model

We introduce the behavioral economic demand framework to a greater audience in the hospitality and tourism research community to initiate a new effort in quantifying hospitality and tourism demand at the disaggregate level, with a focus on understanding more about consumers' cost-benefit assessments in light of both individual differences and environmental factors. Consolidating these considerations, we propose a new conceptual model for researchers who are interested in analyzing and forecasting the demand for hospitality and tourism products/services (Figure 2.2). The core relationship that this framework attempts to uncover is the response of consumer demand to diverse costs involved in consumers' decision-making process. Thanks to the flexibility of the behavioral economic demand models in terms of estimation, group demand curves can be estimated and compared after integrating individual differences or environmental factors, revealing consumers' behavioral heterogeneity in demand at the disaggregate level.

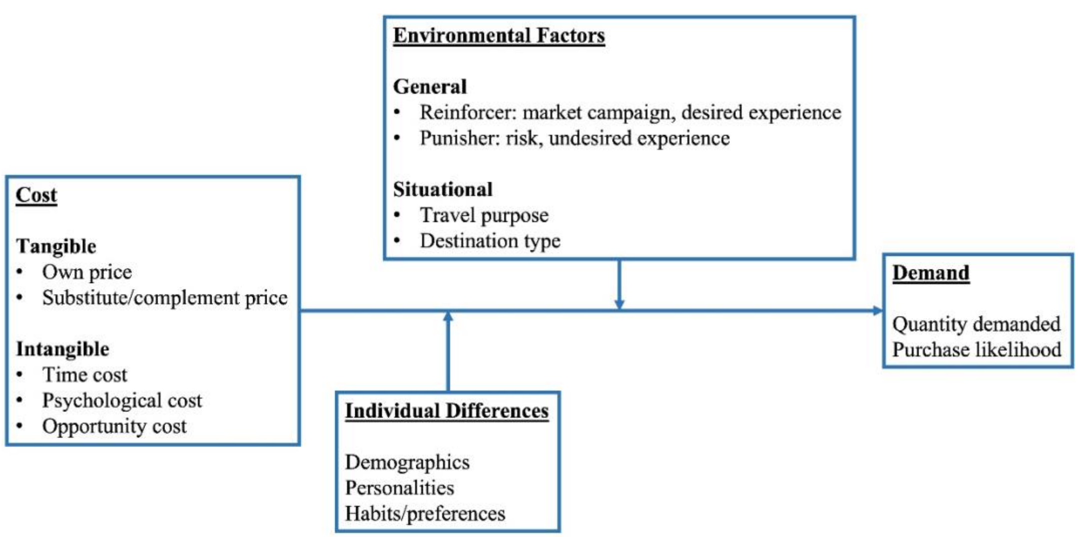


Figure 2.2 A new conceptual model for hospitality and tourism demand studies.

2.4.1 Dependent variable

Consumer demand can be measured in terms of either quantity demanded or purchase likelihood, depending on the nature of the goods. In normal cases, demand curve delineates the relationship between price and quantity demanded, and the quantity demanded implies multiple purchase decisions. However, this measurement is not suitable for slow-moving consumer goods (as opposed to fast-moving consumer goods) as defined by the marketing literature, referring to big-ticket goods that are infrequently purchased, especially in quantity. In this context, the probability of a single purchase is more appropriate as a measure of demand. It is believed that most hospitality and tourism products, such as hotel rooms and travel packages, are mostly slow-moving consumer goods for individuals. However, transportation and food and beverage products may be distinct and belong to the category of fast-moving consumer goods in light of the high frequency at which they are consumed. Both measures are sufficiently informative to exhibit consumption behavior and estimate the demand models (Roma et al., 2016). Nonetheless, it is important to be aware that they deviate from each other regarding the examined decision-making process, because quantity demanded comprises several repeated purchases, whereas purchase likelihood refers to a single purchase. As a result, the meaning of O_{max} with purchase likelihood as the demand is not the maximum total revenue/expenditure, but the expected average revenue/expenditure per capita.

2.4.2 Independent variables

To investigate the micro level of demand at which individual consumption behavior is primarily subject to the cost-benefit analysis, various consequential costs associated with the consumption are taken as independent variables to determine the demand. Based on the generalized notion of price within the behavioral economic demand framework, any relevant quantifiable costs can and should be incorporated into the demand models. We summarize them into tangible and intangible costs. Tangible costs typically refer to the monetary costs or prices of goods. Similar to microeconomic demand analysis, influential prices include not only the product's own price but the prices of related goods (i.e., substitutes and complements). Intangible costs are nonmonetary but potentially quantifiable, and they account for a pronounced part of the total perceived costs for consumers when they are making consumption decisions about hospitality and tourism products. Important intangible costs are time cost (considering the importance of property location and transportation efficiency), psychological cost (considering various risks) and opportunity cost (considering the fundamental tradeoff between leisure and work). Incorporating them into demand modeling moves us one step closer to consumers' real decision-making process.

2.4.3 Grouping variables

The heterogeneity of consumer demand altered by subjective individual differences and objective environmental factors is assessed by making comparisons across the demand curves of the groups at issue, especially their model parameters and essential values. Group demand curves can be estimated by averaging or pooling individual demand data. Accordingly, individual differences and environmental factors act as grouping variables, which can be collected as a part of the hypothetical purchase task questionnaires.

Individual differences are mainly related to consumers' characteristics that may diversify their behavior, including demographics (e.g., age, gender and income), personalities and habits/preferences. Demographics are relatively straightforward to acquire, whereas personalities and habits/preferences may require specific types of measurement techniques. Notably, income, as one essential factor of demographics, is now treated as a grouping variable rather than as an independent variable by convention. The reasons are as follows:

(1) at the micro level, income characterizes consumers; and
(2) differences in income affect not only a consumer's demand at a single price point but the entire demand curve.

Systematic examinations of the effects of individual differences will remedy the deficiency of quantitative justifications in the microeconomic demand theory.

Environmental factors are classified into general and situational factors. Concordant with the stance of behavioral economic, general environmental factors are either reinforcers to strengthen/maintain demand (e.g., market campaign and desired experience) or punishers to weaken/demotivate demand (e.g., risk and undesired experience). By contrast, situational environmental factors impact demand subject to their contexts. These factors are normally decisive, industry-specific characteristics in hospitality and tourism activities, such as travel purpose and destination type. Incorporating environmental factors into the demand analysis will enhance our understanding of tourists and how their decision-making mechanisms interact with their surroundings when purchasing hospitality and tourism products.

2.5 Conclusions and Implications

2.5.1 Conclusions

We present and discuss four critical issues in hospitality and tourism demand studies that primarily relate to aspects of the theoretical foundation that presume rational and homogeneous consumers and econometric models that estimate constant price elasticity on an incomplete demand curve. Therefore, the behavioral economics approach is proposed as a viable solution that acknowledges the effects of individual differences and environmental factors on demand. Its demand framework provides an innovative viewpoint of consumers' cost-benefit assessment of hospitality and tourism products/services, stressing the complete demand curve across individuals and contexts. Behavioral economic demand models have advantageous functional forms that specify elasticity dynamics using a single parameter, balancing thoroughness and interpretability. As a valid data collection method, hypothetical purchase task ensures sufficient individual preferences for the manipulation of various consumption scenarios. Accordingly, a new conceptual model that better facilitates a systematic hospitality and tourism modeling process at the disaggregate level is proposed.

2.5.2 Theoretical implications

As a critical reflection, this study draws researchers' attention to the problems associated with the conventional hospitality and tourism demand analyses. "Behavioral" behavioral economics and an associated demand framework for hospitality and tourism research are proposed for the first time as a viable solution to fill in the identified research gaps. This proposal also encourages researchers to apply the novel research framework to more demand studies not only in hospitality and tourism but also in general consumer behavioral research. Methodologically, we offer a new approach that bridges the gap between aggregate and disaggregate individual demand analysis by deriving group demand curves of consumer segments. The overall analytical framework will have both descriptive and predictive powers, and the heterogeneity of hospitality and tourism consumers' behavioral patterns attributable to individual differences and specific environmental factors can be systematically explored.

2.5.3 Practical implications

Successful demand analysis at the disaggregate level will benefit both private and public sectors involved in the hospitality and tourism businesses. For private sectors, first, the complete demand curve with elasticity dynamics establishes the linkage among price, quantity demanded and revenue with respect to specific hospitality and tourism products/services, implying the optimal pricing point of the product/service and possible shifts in demand and revenue given certain price adjustments. Second, the investigation of the subjective and objective factors' influence on demand can equip hospitality and tourism firms with deeper insights into their target customers and therefore develop more effective business strategies, including differentiated marketing, service failure recovery and crisis management. Third, modeling the prices of related goods/services can effectively quantify the potential substitution and complementary effects to frame the market competition within one (or across several) sector(s), or in further detail, to uncover the possibly dissimilar competition situations for different consumer segments.

The above implications also apply to public policy formulations following the same rationale. Decisions about taxes/rebates to nudge public behavior or facilitate industry development can be supported by the outcomes of the corresponding price adjustments on both individual and group demand curves. Moreover, future investigations into the relationship between demand and consumers' intangible costs, such as the cost of time, will be particularly informative for decision-making on infrastructure investment. In addition, exploring the effects of environmental factors on the shifts of demand curves can help evaluate the efficiency of relevant policies (e.g., destination promotion).

2.5.4 Limitations and future research

It is worth noting that by assuming the exogeneity condition, the proposed conceptual model focuses on the unidirectional causation of tangible and/or intangible costs on hospitality and tourism demand and rules out the possible effect of demand on the costs, which is allowed by some other demand modeling techniques (Assaf et al., 2019). This might be one limitation attached to the conceptual model. Another limitation is that as a conceptual study, this study focuses on theoretical and methodological improvements only without presenting any empirical evidence. Future empirical studies based on the research framework presented here would be beneficial for both academics and practitioners.

The above discussion indicates that hospitality and tourism researchers can benefit from analyzing demand at the disaggregate level. Specifically, they can use behavioral economic models with a view to dissecting the evolution of consumers' cost-benefit analysis on hospitality and tourism products/services in their decision-making processes based on individual differences and environmental factors. An in-depth analysis of essential values represents a step further. Individual essential values can be extracted from individual demand curves and segmented by consumer profiles to portray the types of consumers who value a specific hospitality and tourism product/service at different levels. Furthermore, as an already comprehensive and inclusive parameter to describe demand and its dynamics, essential value itself can be modeled with respect to quantifiable consumer characteristics, such as age and income, among individuals to establish linear or non-linear functional relationships and thus to explore deeper structures of consumer demand. Accordingly, future studies should make good use of essential value to measure consumers' valuation of hospitality and tourism products/services and their demand resilience to various costs.

Another important research direction is to fit the behavioral economic demand models using multiple cost variables. The demand models introduced above are univariate models, with own price being the only explanatory variable for demand. Although a cross-price demand model was proposed in Hursh and Roma (2013), that model remains univariate and does not accommodate own price as a determinant. Nevertheless, there is no doubt that consumer decision-making is shaped by different costs simultaneously. Therefore, more advanced multivariate behavioral economic demand models are needed to comprehensively analyze hospitality and tourism demand at the disaggregate level.

The behavioral economics modeling approach may also pave the way for more accurate hospitality and tourism demand forecasting, because researchers can adopt dynamic econometric models with both cross-sectional and time-series data to study behavioral variations in hospitality and tourism product/service consumption with greater depth and precision. In addition, for aggregate demand forecasting, a good understanding of the disaggregate data extracted from individual consumers/tourists will be beneficial to aggregate hospitality and tourism demand forecasting accuracy improvement. More specifically, a targeted hypothetical purchase task survey with certain scenarios can first be conducted to model individual demand behaviors and obtain the associated essential values. The estimated relationships between essential values and individual differences or environmental factors may then be used for large-scale Bayesian econometric analysis of aggregate hospitality and tourism demand using secondary data. In addition, these identified disaggregate relationships can help researchers either segment the data into groups and forecast their future demand separately or adjust their forecasts under different economic conditions.

Chapter 3 The Heterogeneity of Hotel Demand Curves across Consumers and Contexts

This chapter introduces the second study of this thesis, an empirical research paper under review in the *Journal of Hospitality and Tourism Research*. Section 3.1 establishes the research background. Section 3.2 reviews the literature pertaining to tourism demand modeling and "behavioral" behavioral economics. Section 3.3 details the methodology applied in the study. Section 3.4 presents and discusses the results obtained from the model. Finally, Section 3.5 outlines the research implications and offers managerial recommendations for hotels.

3.0 Abstract

This study constructs hotel demand curves at the disaggregate level to uncover the heterogeneity of demand curves across consumers and during both normal periods and times of crisis, exemplified by the pandemic. The novel demand modeling technique fits nonlinear demand curves, parameterizes elasticity dynamics, and enables the comparison of demand curves by essential value. The demand curves for three hotel types in normal and pandemic situations are fitted and decomposed by consumers' sociodemographics, preferences and risk tolerance. A pandemic makes the demand curve for midscale [upscale] hotels more inelastic [elastic] and mitigates [amplifies] the influence of individual differences on the demand curve, whereas the demand curve for economy hotels is unaffected by the pandemic. The findings offer insights into the business operations of different hotels, including optimal pricing, customized marketing across consumer segments, and business strategies in case of a health crisis.

3.1 Introduction

Building on neoclassical economic demand theory, the existing econometric demand models in hospitality and tourism studies have concentrated on analyzing market demand using aggregate data. These methods are underpinned by the theoretical assumptions that the market demand curve is the horizontal summation of individual demand curves, where individuals are mathematically regarded as homogeneous entities. Although the hospitality and tourism literature on consumer behavior has explored the salient role of sociodemographic factors in shaping tourists' preferences (Chen et al., 2019), the fitting of demand curves has not been disaggregated to consider consumer characteristics. The estimates of quantity demanded and elasticity coefficients using the existing econometric demand models represent average levels only, while the possible heterogeneity across individual demand curves stemming from individual differences has been overlooked. Moreover, the contextual dependence of the shape of the demand curve has been neglected in the existing modeling practices despite findings that many environmental factors, especially a pandemic that could batter the hospitality and tourism industry, are significant in altering consumers' decisions (Kim et al., 2022).

In addition, due to the modeling of incomplete demand curves, the estimation and interpretation of demand elasticity along the demand curve have been restricted to a single elasticity value at the average price, which is insufficient to describe the real economy as the elasticity of demand mostly increases with price (Perloff, 2018). Understanding the dynamics of elasticity along a complete demand curve can help establish the linkages between price, demand and revenue, and provide implications for cost-related business strategies or public policies. Thus, a novel econometric demand model is required to properly parameterize the dynamics of elasticity along the demand curve and depict the demand curves of various consumers and contexts; this will comprehensively reveal consumers' changing cost-benefit evaluations and the heterogeneity of demand curves at the disaggregate level.

An innovative demand framework originating from the behavioral branch of behavioral economics provides a promising solution to fitting complete demand curves at the disaggregate level. There are two branches of research within behavioral economics: the cognitive branch investigates the cognitive biases in decision-making, whereas the behavioral branch examines the environmental influences on behavior (Hursh & Roma, 2013; Magoon & Hursh, 2011). The cognitive branch helps explain the mental processes that influence decision-making. However, it may be difficult to generalize the results of cognitive studies and predict the demand, because the theoretical framework underpinning the cognitive branch of research is based on the point estimation of choices and decisions. Any explored demand pattern is therefore described in a discrete and contingent mode but cannot be well integrated into a universally applicable demand function.

In contrast to the prevalent applications of “cognitive” behavioral economics in hospitality and tourism research (e.g., prospect theory), “behavioral” behavioral economics has received little attention, but it is more relevant to the aforementioned issues in hospitality and tourism demand modeling. First, because the behavioral branch comprehends individual behavior (e.g., consumption) as the consequence of reinforcement by the presence of a certain stimulus (e.g., a product that the consumer values), it stresses the distinctions between individual behaviors caused by different personal valuations and environmental influences. Second, the behavioral branch is based on demand curve analysis to establish an exponential functional relationship between price and demand with a focus on dynamic elasticity, and it enables the fitting of demand curves at any disaggregate level such as individual demand curves and group demand curves. Song and Lin (2023) first introduced “behavioral” behavioral economics and its research methodology to the hospitality and tourism field and developed a new conceptual framework for demand modeling at the disaggregate level. However, no empirical study has been conducted to test the framework.

Therefore, this study aimed to demonstrate the behavioral economics approach to hospitality and tourism demand modeling and to quantitatively capture the influence of individual differences and environmental factors on demand curves. The hotel sector in China was selected as the empirical research context to demonstrate the methodology, with three hotel types subjected to demand modeling. The specific environmental factor analyzed was the consumption situation, which we classified as either a “normal” situation or a “pandemic” situation. Using COVID-19 as a case context, this study was designed to demonstrate the wider applicability of the proposed approach during times of societal disruption and crises such as future pandemics, political instability or other impactful events. This approach provides a valuable tool for the hospitality and tourism industry to respond to shifts in consumer behavior and implement crisis-mode operations amidst instability. Individuals’ demand data were collected and segmented by the consumption situation and/or individual differences, and group demand curves were fitted and compared accordingly.

This is one of the first empirical studies to uncover the heterogeneity of hotel demand curves across consumers and contexts. The innovative methodology shows advantages over traditional econometric methods in two major aspects. First, it allows to fit independent demand curves based on any characteristic variable of interest, thereby giving a more realistic and accurate estimation of the demand of different consumers. Second, the proposed methodology expands the construction of demand curves to a full price range, over which the estimation of demand elasticity is a dynamic process. The model therefore describes the interrelationship between price, demand and revenue and can be used to derive the optimal pricing point. The study also provides insights into hotel business strategies according to different hotel types and market situations.

3.2 Literature Review

3.2.1 Demand curve modeling in tourism economics research

Tourism economics research on demand curve modeling has primarily concentrated on analyzing the effects of demand determinants and forecasting future trends (Song et al., 2009). The vast majority of the currently applied econometric demand models have fitted the market demand curve, which is the summation of the individual demand curves of all of the consumers in the market. According to neoclassical microeconomic demand theory, an individual demand curve is formed by a consumer's optimal choices given their personal preferences and budget constraints. Thus, a market demand curve assumes utility maximization at the individual level and is modeled as the sum of the individual demand of many identical "representative consumers" with statistically average indicators (Thomas, 1985). With this theoretical underpinning, most hospitality and tourism demand modeling studies have been based on aggregate data and have treated the market as a homogeneous group (Qiu et al., 2020). Individual differences, such as age, gender and income, have been indexed to market average values or proportions and used as explanatory variables to model the market demand curve and estimate their effects on average market demand (Aguilar & Díaz, 2019).

Little research has been conducted to construct disaggregate demand curves by segregating the market demand data based on consumer characteristics and to identify the heterogeneity of those demand curves within individual consumers or consumer segments. The individual/group demand curves are likely to be notably different from each other instead of identical in shape and parameters as estimated before, as consumers allocate varying budgets and have distinct personal preferences for a certain product because of their sociodemographic characteristics (Barbieri &

Mahoney, 2010) and past experiences (Masiero & Qiu, 2018). However, when integrating individual differences into the econometric demand models, researchers have rarely focused on the segmentation of consumers based on individual characteristics and its significant influence on the shape of the demand curve at the disaggregate level. The demand heterogeneity across consumer groups has been explored only concerning consumer utility, which has been modeled using discrete choice techniques to explain an individual's or a group's choice from alternatives (Kemperman, 2021).

Although choice and demand are intuitively similar and are both considered part of the demand analysis, they are essentially disparate concepts and are expressed in different mathematical terms in the modeling processes (utility value vs. quantity demanded). Therefore, although discrete choice models have been used to analyze choices at the individual level, the derived results cannot be regarded as equivalent to the demand curve of the same individual for the chosen product, nor can any direct statistical comparisons be made between the parameters of a choice model and those of an econometric demand model. The demand curves of heterogeneous consumer groups have not yet been directly modeled, although such demand models would produce useful economic information, such as elasticities, revenue and demand forecasts.

Moreover, consumers' demand curves are likely to be influenced by environmental changes, especially in the occurrence of a pandemic. This argument is bolstered by the observed asymmetric demand pattern throughout a business cycle, with mismatched elasticities between fast- and slow-growth periods (Smeral, 2018). Nevertheless, there have been few studies in hospitality and tourism research to explicitly examine how environmental factors such as COVID-19 and other pandemics or crises would affect the shape of the entire demand curve, given that most of the relevant studies have paid attention to the temporarily dropped demand only (He et al., 2022).

Another issue is that traditional econometric demand models generally construct incomplete demand curves which yield merely point estimation of quantity demanded and demand elasticity at around the market average price, whereas the complete shape of a demand curve and the decay of demand over the full price range have not been fully investigated. Constructed over a very narrow price range, the hotel/tourism demand curves have seemed to be sufficiently fitted as logarithmically linear forms with constant price elasticity (Song et al., 2019). Even when a dynamic elasticity parameter is functionally allowed, researchers tend to calculate the elasticity coefficient at the average price; otherwise, there would have been a series of statistically inconsequential elasticity coefficients at various price points. As a result, the shape of the demand curve has not been successfully linked up with the shape of the total revenue curve to reflect the pricing strategy.

However, economists widely believe that the elasticity of demand increases with price on most demand curves (Perloff, 2018), implying that the complete demand curve is nonlinear on the logarithmic coordinates. Thus, it is rather necessary to improve the demand modeling methodology to construct complete demand curves over the entire price range and parameterize the dynamics of elasticity along the demand curve. In this way we can get a complete image of the shape of a demand curve at all price points, efficiently describe the demand curve using parameters, and establish the linkages between price, demand and revenue to ultimately make more informed economic decisions.

3.2.2 Behavioral economic demand curve analysis

To address the problems stated above and model demand curves at the disaggregate level, in this study, we used a behavioral economics approach. This approach is not based on the branch of behavioral economics popular in the social sciences, which introduces cognitive psychology to economics to explore how humans' cognitive biases affect their rational decision-making and is known as "cognitive" behavioral economics. The branch relevant to this study is referred to as "behavioral" behavioral economics (Song & Lin, 2023). It originates from the introduction of economic theories to operant psychology to quantify the operant behavior of humans and animals. This branch is less widely known, as discussion of it has generally been limited to the field of behavioral psychology.

Apart from the different focuses (cognitive biases vs. environmental influences), the behavioral branch has a critical advantage over the cognitive branch in exploring demand heterogeneity at the disaggregate level. In contrast with the point estimation of discrete and contingent choices in "cognitive" behavioral economics, "behavioral" behavioral economics has developed a demand model to specify the continuous functional relationship between demand and its determinants, giving its empirical results greater descriptive power and more straightforward implications for mass economic activities than the cognitive branch. The dynamics of elasticity is parameterized in the model to reflect consumers' cost-benefit evaluations and is applied as an indicator to interpret and compare the demand curves. Consequently, the demand heterogeneity can be specifically quantified and systematized within one quantitative framework.

In "behavioral" behavioral economics, economic goods are likened to reinforcers of consumption behavior, and the strength of reinforcement against costs reflects the value of goods. Behaviorists have used demand curves to describe the interaction between costs and reinforcement and the scale of the reinforcing efficacy. A complete demand curve is mapped by two fundamental parameters: demand intensity (the demand at zero price, Q_0), which dictates the starting point, and demand elasticity (the slope of the demand curve), which dictates the rate of decay of demand. The endpoint, where demand reaches zero, is called the breakpoint. Hursh and Silberberg (2008) demonstrated that a demand curve on logarithmic coordinates has a downward-sloping concave shape with an accelerating rate of decay. This indicates that the demand curve displays an elasticity coefficient that progressively increases with price, implying an inverted U-shaped total revenue curve. The price at which revenue reaches a peak (O_{max}) is designated by P_{max} and is expected to appear at the point of unit elasticity.

Estimating demand elasticity as a single coefficient is insufficient, although this practice has been common in hospitality and tourism demand studies because of researchers' preference for the double-log functional form (Song & Lin, 2010) or desire to average dynamic point elasticities to statistically cover a great deal of information in one parameter (Li et al., 2006). Behavioral economic demand models overcome this problem by employing one parameter (α) to specify the change rate of demand elasticity over the price range. Therefore, elasticity is viewed on a continuum rather than as a coefficient. Changes in elasticity along the demand curve reflect the value of goods, termed the essential value. A higher essential value signifies a lower rate of increase in elasticity and a greater resistance of demand to price, suggesting that the good strengthens or maintains consumption behavior to a larger extent (Hursh & Silberberg, 2008).

The hypothetical purchase task has been a prominent data collection method in "behavioral" behavioral economics. Data collected by hypothetical purchase tasks provide a range of sensitive and instructive measurements for assessing the value of goods and the drive of consumption. The advantages of hypothetical purchase tasks lie in their flexibility in manipulating various consumption scenarios to explore the impacts of external stimuli on demand curves at different levels of aggregation – individual, group, market, and population. It is instrumental when direct measurement of actual demand in laboratory settings or real-world markets is impractical or unethical (Roma et al., 2016). In a hypothetical purchase task, participants are asked to state their demand at a series of predetermined price points in a certain scenario and under certain assumptions and restrictions. Demand can be measured in terms of both quantity and probability depending on how frequently the goods are purchased in everyday life. The probability format has been applied in many relevant studies (Reed et al., 2016) and has been proven equally suitable and informative for analyzing demand curves as the quantity format, although it tends to yield higher behavioral economic value measures (Roma et al., 2016).

The hypothetical purchase task has been an instrumental technique for capturing the heterogeneity of demand curves at the disaggregate level. Previous studies in "behavioral" behavioral economics have recognized variations in demand curves across individuals of different genders (Lemley et al., 2016; Mulhauser et al., 2018), incomes (Koffarnus, Wilson & Bickel, 2015), and consumption habits/experiences (Schwartz et al., 2019, 2021; Strickland et al., 2017). The impacts of various environmental factors on demand curves have also been described, including future responsibilities (Ferguson et al., 2021), environmental cues/narratives (Bickel et al., 2018; Bulley & Gullo, 2017), and behavioral/pharmacological interventions (Schlienz et al., 2014), among others.

A hypothetical purchase task is the best alternative to secondary demand data given the data deficiency over a wide price range. The validity and reliability of hypothetical purchase task technique are supported by its temporal stability and the significant correlations found between the stated demand and self-reported behavior of participants (Murphy et al., 2009). Although behavioral economic demand models and hypothetical purchase tasks have been used primarily to examine addictive behaviors (Kaplan et al., 2018), they have also been used effectively to analyze demand for various generic goods, such as chocolate (Chase et al., 2013), air-flight Internet access (Broadbent & Dakki, 2015) and snack foods (Epstein et al., 2010). Overall, however, the use of the behavioral economics approach for demand modeling has remained in its infancy in many fields of research.

The present study is one of the first attempts to analyze hotel demand using the behavioral economics approach. This approach enables econometric demand modeling at the disaggregate level to quantify the heterogeneity of demand curves across consumers and contexts. Consumers are not regarded as homogeneous entities but are treated as heterogeneous groups in terms of individual differences to fit group demand curves over the full price range. In addition, this study examines to what extent a major environmental factor influences consumers' consumption decisions and reshapes group demand curves. Integrating an experimental design, the demand curves and consumer segmentation, this study demonstrates an approach that can be readily applied as a demand modeling tool for more than just typical products; it can also be tailored to individual businesses.

3.3 Methodology

3.3.1 Research design

This study focused on three hotel types: economy (1-/2-star), midscale (3-/4-star), and upscale (5-star). The environmental factor analyzed was a pandemic, given its significant impact and disturbance of the hospitality and tourism industry worldwide. We framed a binary treatment of the consumption situation using COVID-19 as a representative case example to illustrate the demand pattern during societal disruption and crises. As COVID-19 has had a wide-ranging and enduring influence on Chinese consumers' behavior, the Chinese market has been a suitable context to examine how the demand curves have shifted because of a pandemic. The specific type of consumer demand modeled was domestic hotel demand in China. A 3 (*hotel type*: economy/midscale/upscale) × 2 (*consumption situation*: normal/pandemic) between-subjects experiment was conducted using randomly assigned hypothetical purchase tasks.

3.3.2 Hypothetical purchase task questionnaire

Individual demand data were collected using hypothetical purchase task questionnaires. The questionnaire for each experimental group contained an image representing the given hotel type, a written description of the consumption scenario, the assumptions, and 13 predetermined price points where the participants were asked to state their demand. Demand was measured by the probability of a single purchase. This was deemed to be more appropriate than quantity demanded as a means of measuring slow-moving consumer goods like hotels, which are not frequently purchased in large quantities by individual consumers (Roma et al., 2016). The questionnaire (Appendix A) was developed in Chinese. Examples of English-translated scenario descriptions for economy hotels in the normal and pandemic situations are as follows.

> *Normal situation:*
>
> Imagine that you are living your normal life before the COVID-19 pandemic. You plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city for a 1-week leisure trip. You have your eye on a typical standard room in an economy hotel as one of your possible accommodation choices. (Note: Economy hotels are equivalent to 1-/2-star hotels.)
>
> *Pandemic situation:*
>
> The COVID-19 pandemic has not yet subsided in China; outbreaks of varying scales have continued to occur across the country since 2021. In this situation, you plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city that is not currently experiencing an outbreak for a 1-week leisure trip. You have your eye on a typical standard room in an economy hotel as one of your possible accommodation choices. (Note: Economy hotels are equivalent to 1-/2-star hotels.)

Two manipulation check questions were presented following the scenario description. The manipulation of hotel type was measured by asking about the cost of staying in certain hotel type, while the participants' rating of the potential health risk in the described trip was used to measure the manipulation of consumption situation, both on a 7-point Likert scale. The statistics confirmed that the manipulations of both hotel type (F = 679.33, p = .00) and consumption situation ($t_{economy}$ = -10.49, $t_{midscale}$ = -11.54, $t_{upscale}$ = -11.91, p = .00) were successful.

The next section was the main purchase task. Under all scenarios, the participants were asked to assume that (1) they had no access to any economy hotels other than their preferred hotel as described in the scenario, (2) their income and savings remained unchanged, and (3) price variation would not affect the room or service quality. Based on those assumptions, the participants stated their purchase probability (0%~100%) if the standard room rate in their preferred economy hotel was ¥0, ¥80, ¥100, ¥130, ¥180, ¥230, ¥300, ¥400, ¥520, ¥670, ¥870, ¥1,150 and ¥1,500, respectively. The minimum price was ¥0, and the maximum price was five times the average market price to locate zero demand, according to pilot tests. The progression of prices generally followed a logarithmic scale. Following the same procedure, the price points for the midscale hotel groups were ¥0, ¥120, ¥150, ¥200, ¥260, ¥350, ¥450, ¥580, ¥770, ¥1,000, ¥1,300, ¥1,700 and ¥2,250, and those for the upscale hotel groups were ¥0, ¥160, ¥200, ¥270, ¥350, ¥460, ¥600, ¥780, ¥1,000, ¥1,300, ¥1,750, ¥2,300 and ¥3,000.

Lastly, there were questions about sociodemographic characteristics, consumption preferences (frequent accommodation choice) and risk tolerance. The measure of risk tolerance was adopted from Williams et al. (2022), and the standardized factor scores were derived with high factor loadings (0.893) and a satisfactory internal consistency (Cronbach's $\alpha = 0.678$). The participants assigned to the three groups under the pandemic scenario were also guided to list the main factors that they would consider when choosing accommodation for leisure trips during a pandemic. The texts were coded by keywords and ranked by frequency.

3.3.3 Participants

The target population was Chinese adults. Participants were recruited through a reputable online research firm, Credamo, and each was randomly assigned to one of the six experimental groups to complete the hypothetical purchase task online. Two pilot studies, each having 120 sample responses, were conducted in April 2022 to test and refine the research design and questionnaire components. In the first round of main data collection (April–May 2022), the questionnaire was released and opened to the entire sample pool of the research firm. The participant characteristics and distributions were then scrutinized, and the questionnaire was republished in the second round (June 2022) to target specific groups that lacked sufficient samples. Finally, 822 valid responses were obtained (see Table 3.1), with few sizeable differences in participant distribution across categorized groups.

Table 3.1 Sample distribution in experimental groups.

Experimental groups		**Sample size**
Economy hotels	Normal	136
	Pandemic	135
Midscale hotels	Normal	140
	Pandemic	138
Upscale hotels	Normal	136
	Pandemic	137
Total		**822**

Table 3.2 provides the demographic profile of the participants. Women represented 54% of the participant pool. Ages ranged from 18 to 78 years (mean = 36.46). The median annual household income was between ¥137,000 and ¥239,000. More than half of the participants held a bachelor's degree, were wage-employed, and had children under the age of 18 years.

Table 3.2 Sample sociodemographic characteristics.

	Frequency	**Percentage**
Gender		
Female	444	54.0
Male	378	46.0
Age		
18 ~ 25 years	146	17.8
26 ~ 35 years	280	34.1
36 ~ 45 years	190	23.1
46 ~ 55 years	134	16.3
≥ 56 years	72	8.8
Income		
< ¥68,000	104	12.6
¥68,000 ~ ¥98,000	113	13.7
¥98,000 ~ ¥137,000	179	21.8
¥137,000 ~ ¥239,000	248	30.2
> ¥239,000	178	21.7
Education		
Junior college or lower	163	19.8
Bachelor's degree	527	64.1
Postgraduate degree	132	16.1
Employment		
Wage-employed in private enterprises	324	39.4
Wage-employed in state-owned enterprises	158	19.2
Wage-employed in public institutions or civil service	107	13.0
Wage-employed in foreign-owned enterprises	44	5.4
Self-employed	52	6.3
Student	101	12.3
Retired or not in the labor force	36	4.4
No. of children under 18 years old		
0	376	45.7
1	354	43.1
2	92	11.2

Preliminary chi-square analyses were conducted to check the sociodemographic distributions across the six experimental groups. The statistics confirmed that the groups did not significantly differ in their distributions of gender ($X^2(5) = 3.85$, $p = .57$), age interval ($X^2(20) = 13.41$, $p = .86$), income interval ($X^2(20) = 20.18$, $p = .45$), education ($X^2(10) = 6.03$, $p = .81$), or employment ($X^2(30) = 31.35$, $p = .40$). The one-way analysis of variance tests verified that all six groups were equivalent regarding mean age ($F(5) = 0.81$, $p = .54$) and average number of children under 18 years old ($F(5) = 0.99$, $p = .43$).

3.3.4 Data analysis

The behavioral economic demand model used to fit the demand curves was the exponentiated model (Koffarnus, Franck, et al., 2015), written as follows:

$$Q = Q_0 10^{k(e^{-\alpha Q_0 P}-1)}, \tag{3.1}$$

where P is price, Q is demand, Q_0 is demand intensity, k is a span parameter specifying the range of logarithmic demand values, and α stipulates the change rate of the price elasticity of demand. Compared with the traditional exponential model that fits data on the logarithmic scale (Hursh & Silberberg, 2008), this model is superior in that zero consumption values can be directly processed without the need for replacement. The derived parameter Q_0 was limited by an upper bound of 100% as the maximum value of probability.

According to Hursh (2014), the estimated k and α from Equation 3.1 were put into Equation 3.2 to calculate the essential value (EV):

$$EV = \frac{1}{100\alpha k^{1.5}}. \tag{3.2}$$

The above equation adjusts for k based on an iteration solution to make the essential value a value yardstick for reinforcers across experiments that is inversely proportional to α, independent of k, and positively related to the price of unit elasticity P_{max}. In addition to the model parameters and key indicators, which include P_{max}, O_{max} and R^2, two measures of breakpoints, BP_1 (the highest observed price to yield any demand) and BP_0 (the lowest observed price to yield zero demand), were reported. The breakpoint price represents the maximum amount consumers are willing to pay, serving as a natural ceiling for pricing strategies and a crucial indicator in predicting market reactions to price changes and economic shifts. A lower breakpoint price compared to competitors may indicate higher price sensitivity among customers or a more competitive market environment.

Group demand curves were modeled by fitting the mean data to compare the parameters and explore possible changes arising from individual differences between consumers and changes in the consumption situation. The significance of the differences in demand curves across groups were obtained through an extra sum-of-squares F-test, with the null hypothesis that α was identical across all groups. The rejection of the null hypothesis meant that the tested groups did not share the same demand curve. Warranted post-hoc F-tests were conducted to identify significant differences between groups.

3.4 Results and Discussion

The demand curves across the three hotel types differed significantly (F = 581.12, p = .00). Thus, differences in demand curves between normal and pandemic situations were tested for each hotel type separately. Significantly different demand curves were generated for midscale hotels (F = 17.38, p = .00) and upscale hotels (F = 15.04, p = .00), but the demand curve for economy hotels did not differ significantly between the two situations (F = 1.37, p = .24). Figure 3.1 displays the demand curves of all six experimental groups.

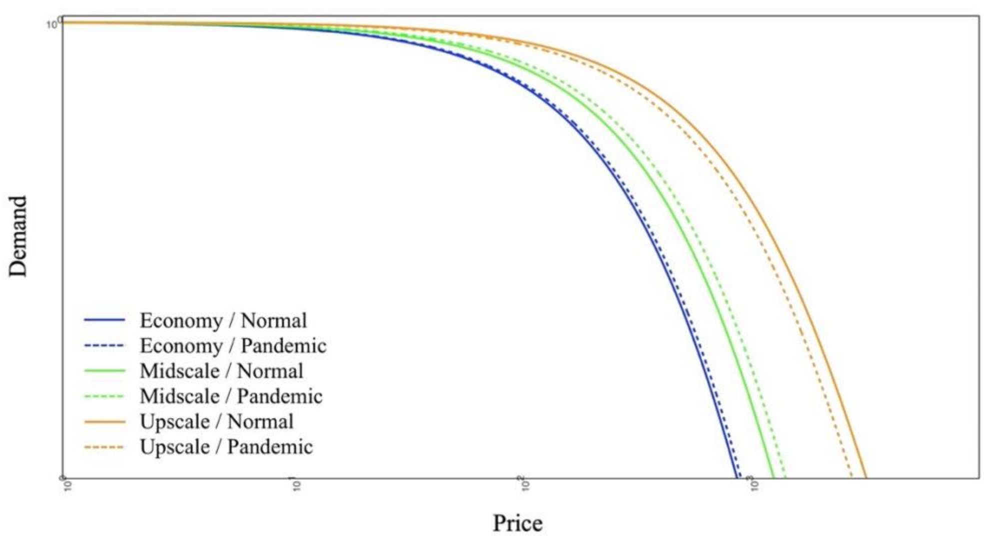
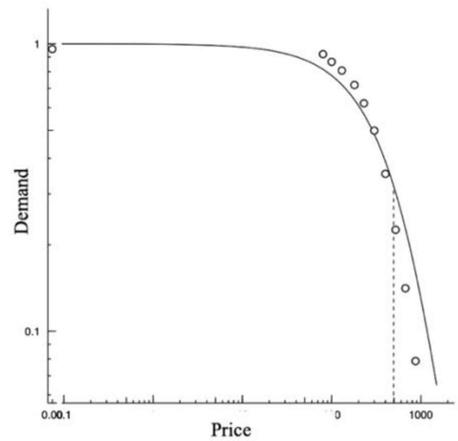


Figure 3.1 Demand curves for three hotel types in normal vs. pandemic situations.

3.4.1 Group demand curves by consumption situation

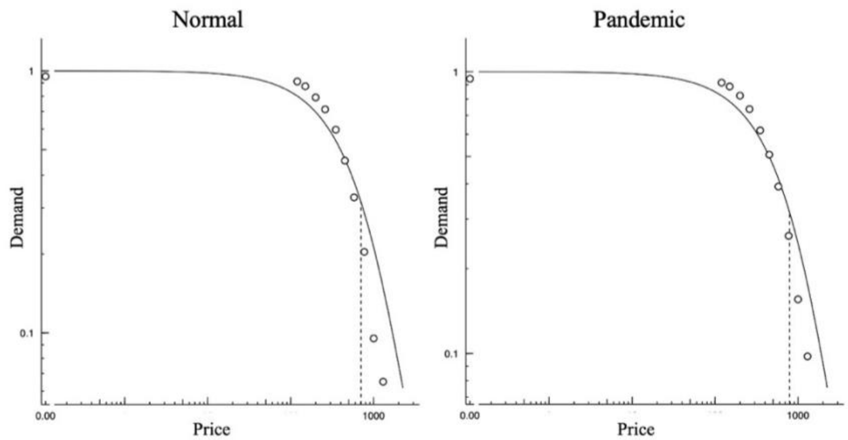
The pandemic situation did not substantially alter the demand curve for economy hotels. Figure 3.2 presents the fitted demand curve, modeling performance and derived parameters. The dotted line under the curve represents the point of unit elasticity. The demand elasticity for economy hotels exhibited a relatively high rate of increase with price compared with the other hotel types, resulting in an essential value as low as 5.92. The estimated optimal pricing point was ¥495. However, the fast decay rate for demand indicated a swift drop in consumer demand in the ¥716 to ¥929 price range.



	R^2	Q_0 (%)	α (10^{-4})	EV	P_{max} (¥)	O_{max} (¥)	BP_1 (¥)	BP_0 (¥)
Overall	0.96	100	5.04	5.92	495	158	716	929

Figure 3.2 Model results by consumption situation: economy hotels.

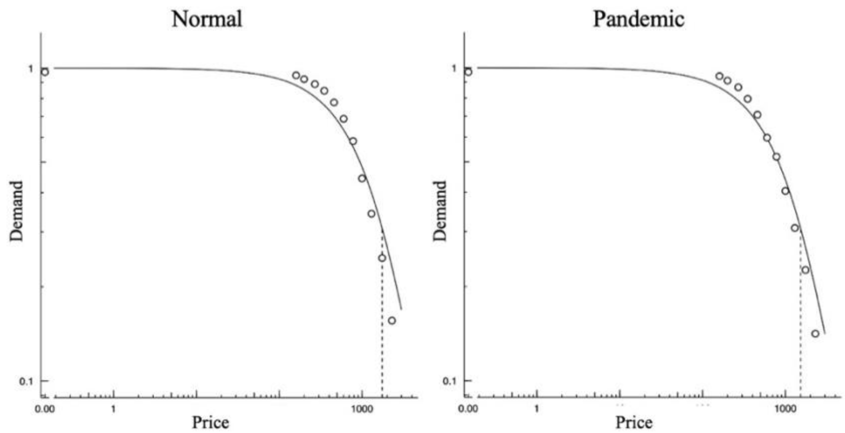
In the normal situation, the demand elasticity for midscale hotels increased at a rate of α = 4.03 (10^{-4}) and reached unit elasticity at a price of ¥702. The demand curve for midscale hotels was responsive to the focal environmental factor, with a significantly slower rate of elasticity increase in the pandemic situation than in the normal situation. The inelastic region under the demand curve expanded, suggesting that consumer demand for midscale hotels became more resilient. The essential value of midscale hotels increased from 8.58 to 9.68 during the pandemic situation, with a higher optimal pricing point at ¥792 (see Figure 3.3).



	R^2	Q_0 (%)	α (10^{-4})	EV	P_{max} (¥)	O_{max} (¥)	BP_1 (¥)	BP_0 (¥)
Normal	0.95	100	4.03	8.58	702	222	1,000	1,380
Pandemic	0.96	100	3.57	9.68	792	250	1,136	1,519

Figure 3.3 Model results by consumption situation: midscale hotels.

Figure 3.4 presents the fitted demand curves for upscale hotels. In the normal situation, the demand elasticity grew with price at a low rate, indicating a high essential value. The estimated optimal price was ¥1,758. Consumer demand declined to zero given a price between ¥1,988 and ¥2,731. In contrast to midscale hotels, upscale hotels in the pandemic situation showed a significantly higher rate of elasticity increase compared with normal times, reducing the optimal pricing point (¥1,527) and the breakpoints. Consequently, the essential value of upscale hotels became smaller in the pandemic situation.



	R^2	Q_0 (%)	α (10^{-4})	EV	P_{max} (¥)	O_{max} (¥)	BP_1 (¥)	BP_0 (¥)
Normal	0.96	100	2.21	22.48	1,758	539	1,988	2,731
Pandemic	0.97	100	2.55	19.52	1,527	468	1,875	2,546

Figure 3.4 Model results by consumption situation: upscale hotels.

This analysis exemplifies the effectiveness of essential value as a standardized index to quantify the value of goods by specifying the dynamics of demand elasticity along a demand curve, making different goods comparable with each other. In general, upscale hotels were valued highest by consumers, followed by midscale and then economy hotels. However, the demand curves for the three hotel types were affected by a pandemic to various extents. The pandemic situation did not alter the demand curve for economy hotels, but it did cause a slower [faster] exponential decay rate in the demand curve for midscale [upscale] hotels. These situational changes indicated that under the influence of a pandemic, consumer demand for midscale [upscale] hotels became more inelastic [elastic] at all prices, as indicated by a larger [smaller] essential value and a higher [lower] optimal pricing point.

The above differences between the demand curves can be explained with reference to the participants' questionnaire responses concerning their main considerations when choosing accommodation during a pandemic. As shown in Table 3.3, epidemic prevention conditions and measures in a hotel were the participants' priority. While location remained a top consideration, a hotel's comfort level was also very important because the participants were aware that they might have to stay in the hotel for a long time in the event of a city lockdown. Price and hygiene held almost equal importance as each other. In this regard, midscale hotels appeared to offer a good balance between cost and risk reduction and were therefore preferred during the pandemic.

Conversely, staying in an upscale hotel might incur a considerable financial risk if there was a sudden lockdown. Economy hotels differed from midscale and upscale hotels in goods and services provided. An economy hotel is analogous to a necessity good in the lodging products sector, designed to meet fundamental needs and having a constant value. Therefore, the demand curve for economy hotels remained stable regardless of the state of the market. In sum, the occurrence of a pandemic increased consumers' perceived health and financial risks when booking a hotel stay, thereby affecting the corresponding demand curves.

Table 3.3 Ranked consumer considerations when making an accommodation choice amid a pandemic.

Keywords	Frequency (Percentage)
Epidemic prevention conditions/measures	213 (50.7%)
Location, transportation convenience	186 (44.3%)
Interior environment, equipment, comfort level	174 (41.4%)
Price, value for money	153 (36.4%)
Hygiene	149 (35.5%)
Security/privacy	93 (22.1%)
Quality of service/management	89 (21.2%)
Epidemic risk/policy of the situated city	68 (16.2%)
Brand, reputation	36 (8.6%)
Food and beverages	10 (2.4%)

The results confirm the finding that the impact of a pandemic on the demand for high-end [low-end] hotels was the most [least] significant (He et al., 2022). However, in terms of demand elasticity, studies have focused on industry-wide elasticity and thus have not investigated variations in demand elasticity between different hotel types resulting from the effects of pandemics or other crises. One exception is Canina and Carvell (2005), who found an inverse relationship between price elasticity and hotel type in a normal period. Therefore, the results of the current study provide deeper insights into pre- and post-crisis hotel demand and its elasticity in relation to hotel types than offered by the literature.

3.4.2 Disaggregate demand curves of consumer groups

The influence of individual consumer differences on demand curves was examined by disaggregating the participants based on selected characteristic variables and testing the significant differences across group demand curves. The demand intensity Q_0 was estimated at 100% in all cases.

According to Table 3.4, gender, age, income and risk tolerance significantly affected the shape of the demand curve for economy hotels. Males generated a more inelastic demand curve than females, with a larger essential value and optimal price, and people aged 26 years and above valued economy hotels more than those aged 18-25 years. Unsurprisingly, income and risk tolerance positively [negatively] affected the essential value [demand elasticity], yet no significant difference in demand curves was detected among the middle- and high-income (above ¥98,000) groups. Differences in consumer preferences did not affect the demand curve.

Table 3.4 Model results by consumer group: economy hotels.

	F	R^2	α (10^{-4})	EV	P_{max} (¥)	O_{max} (¥)
Gender	21.72^{***}					
Female		0.96	5.36	5.59	467	150
Male		0.96	4.69	6.39	534	171
Age	43.35^{***}					
18 ~ 25 years		0.95	7.31	4.10	342	110
26 ~ 35 years		0.95	4.63	6.47	541	173
36 ~ 45 years						
46 ~ 55 years						
≥ 56 years						
Income	48.27^{***}					
< ¥68,000		0.97	7.79	3.85	322	103
¥68,000 ~ ¥98,000		0.97	6.47	4.63	387	124
¥98,000 ~ ¥137,000		0.94	4.51	6.65	555	178
¥137,000 ~ ¥239,000						
> ¥239,000						
Preference	0.98	0.96	5.06	5.92	495	158
Risk tolerance	50.32^{***}					
Below-average		0.96	5.71	5.25	438	140
Above-average		0.95	4.64	6.46	539	173

*** $p < .001$.

For midscale and upscale hotels, the impact of individual differences was assessed in both normal and pandemic situations. As reported in Table 3.5, all the characteristics except gender significantly differentiated the demand curve for midscale hotels in both situations. Gender was a significant influencing factor in the normal situation, with females generating a more elastic demand curve than males, but the impact of gender vanished in the pandemic situation. Young adults (18-25 years) and senior adults (56 years or above) valued midscale hotels the least in the normal situation, but the valuation reported by senior adults greatly increased in the pandemic situation. In both situations, people aged 26-35 years attached the greatest essential value to midscale hotels compared with the other age groups. The positive correlation between income and essential value was confirmed. However, the segmentation of income groups differed between the two situations, most noticeably in the considerable increase in the essential value for middle-income people (¥98,000 ~ ¥137,000) during the pandemic. People who preferred to stay in bed-and-breakfast inns (B&Bs) and economy hotels had the most elastic demand curve in the normal situation but experienced the greatest increase in essential value for midscale hotels in the pandemic situation, such that there was no difference between their essential value and that of frequent customers of midscale hotels. Risk tolerance exerted a negative influence on the rate of elasticity increase. People with an above-average level of risk tolerance valued midscale hotels markedly higher in the pandemic situation than in the normal situation, while the valuation of the below-average risk tolerance group remained relatively stable.

Table 3.5 Model results by consumer group: midscale hotels.

<table>
<tr><th rowspan="2"></th><th colspan="2">F</th><th colspan="2">R^2</th><th colspan="2">α (10^{-4})</th><th colspan="2">EV</th><th colspan="2">P_{max} (¥)</th><th colspan="2">O_{max} (¥)</th></tr>
<tr><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th></tr>
<tr><td>**Gender**</td><td>35.29^{***}</td><td>0.05</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Female</td><td></td><td></td><td>0.93</td><td rowspan="2">0.96</td><td>4.46</td><td rowspan="2">3.57</td><td>7.76</td><td rowspan="2">9.68</td><td>635</td><td rowspan="2">792</td><td>201</td><td rowspan="2">250</td></tr>
<tr><td>Male</td><td></td><td></td><td>0.96</td><td>3.53</td><td>9.80</td><td>802</td><td>253</td></tr>
<tr><td>**Age**</td><td>44.46^{***}</td><td>14.26^{***}</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>18 ~ 25 years</td><td></td><td></td><td rowspan="2">0.94</td><td>0.93</td><td rowspan="2">6.22</td><td>4.54</td><td rowspan="2">5.56</td><td>7.62</td><td rowspan="2">455</td><td>623</td><td rowspan="2">144</td><td>197</td></tr>
<tr><td>≥ 56 years</td><td></td><td></td><td rowspan="3">0.94</td><td rowspan="3">3.51</td><td rowspan="3">9.85</td><td rowspan="3">806</td><td rowspan="3">255</td></tr>
<tr><td>36 ~ 45 years</td><td></td><td></td><td rowspan="2">0.94</td><td rowspan="2">4.07</td><td rowspan="2">8.50</td><td rowspan="2">695</td><td rowspan="2">220</td></tr>
<tr><td>46 ~ 55 years</td><td></td><td></td></tr>
<tr><td>26 ~ 35 years</td><td></td><td></td><td>0.92</td><td>0.97</td><td>3.06</td><td>3.08</td><td>11.31</td><td>11.24</td><td>926</td><td>920</td><td>293</td><td>291</td></tr>
<tr><td>**Income**</td><td>47.17^{***}</td><td>22.45^{***}</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>< ¥68,000</td><td></td><td></td><td>0.93</td><td>0.93</td><td>6.89</td><td>5.86</td><td>5.02</td><td>5.91</td><td>411</td><td>483</td><td>130</td><td>153</td></tr>
<tr><td>¥68,000 ~ ¥98,000</td><td></td><td></td><td rowspan="2">0.92</td><td>0.94</td><td rowspan="2">4.60</td><td>4.31</td><td rowspan="2">7.53</td><td>8.02</td><td rowspan="2">616</td><td>657</td><td rowspan="2">195</td><td>207</td></tr>
<tr><td>¥98,000 ~ ¥137,000</td><td></td><td></td><td rowspan="3">0.95</td><td rowspan="3">3.21</td><td rowspan="3">10.77</td><td rowspan="3">881</td><td rowspan="3">278</td></tr>
<tr><td>¥137,000 ~ ¥239,000</td><td></td><td></td><td rowspan="2">0.94</td><td rowspan="2">3.12</td><td rowspan="2">11.09</td><td rowspan="2">908</td><td rowspan="2">287</td></tr>
<tr><td>> ¥239,000</td><td></td><td></td></tr>
<tr><td>**Preference**</td><td>31.28^{***}</td><td>6.66^{***}</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>B&Bs</td><td></td><td></td><td rowspan="2">0.94</td><td rowspan="3">0.94</td><td rowspan="2">4.81</td><td rowspan="3">3.71</td><td rowspan="2">7.19</td><td rowspan="3">9.33</td><td rowspan="2">589</td><td rowspan="3">764</td><td rowspan="2">186</td><td rowspan="3">241</td></tr>
<tr><td>Economy hotels</td><td></td><td></td></tr>
<tr><td>Midscale hotels</td><td></td><td></td><td>0.94</td><td>3.84</td><td>9.01</td><td>737</td><td>233</td></tr>
<tr><td>Upscale hotels</td><td></td><td></td><td>0.97</td><td>0.94</td><td>2.38</td><td>2.79</td><td>14.54</td><td>12.39</td><td>1,190</td><td>1,014</td><td>376</td><td>320</td></tr>
<tr><td>**Risk tolerance**</td><td>13.16^{***}</td><td>63.09^{***}</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Below-average</td><td></td><td></td><td>0.93</td><td>0.94</td><td>4.35</td><td>4.37</td><td>7.96</td><td>7.92</td><td>652</td><td>648</td><td>206</td><td>205</td></tr>
<tr><td>Above-average</td><td></td><td></td><td>0.96</td><td>0.96</td><td>3.77</td><td>3.09</td><td>9.19</td><td>11.19</td><td>752</td><td>915</td><td>238</td><td>289</td></tr>
</table>

*** $p < .001$.

All the characteristics generated significant impacts on the demand curve for upscale hotels in both normal and pandemic situations. Females valued upscale hotels less than males did, but females' valuation was more vulnerable to a pandemic, dropping by a larger magnitude than that of males. Age segmentation in the normal situation revealed a simple two-group result, with 26 years old as the dividing point. However, this pattern did not hold in the pandemic situation, as there was a sizable decrease in the essential value among middle-aged and senior adults compared with young adults. The positive effect of income on essential value was also verified. In the normal situation, the demand curve of individuals in the highest income group (above ¥239,000) was significantly more inelastic than the curves of the other groups. The occurrence of a pandemic altered this pattern by shifting the cut-off income level to ¥137,000, suggesting a decline in upscale hotels' essential value among high-income consumers. Participants who preferred economy and midscale hotels showed the same demand curve for upscale hotels, with a relatively small essential value, irrespective of the consumption situation. People with a preference for B&Bs valued upscale hotels as much as frequent customers of upscale hotels in the normal situation but drastically less in the pandemic situation. Frequent customers consistently showed the most inelastic demand of all customers. Risk tolerance negatively affected demand elasticity, and people with below-average levels of risk tolerance lowered their valuation in the pandemic situation to a greater extent than people with above-average risk tolerance (see Table 3.6).

Table 3.6 Model results by consumer group: upscale hotels.

<table>
<tr><th rowspan="2"></th><th colspan="2">F</th><th colspan="2">R^2</th><th colspan="2">α (10^{-4})</th><th colspan="2">EV</th><th colspan="2">P_{max} (¥)</th><th colspan="2">O_{max} (¥)</th></tr>
<tr><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th><th>Normal</th><th>Pandemic</th></tr>
<tr><td>**Gender**</td><td>11.02***</td><td>36.71***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Female</td><td></td><td></td><td>0.96</td><td>0.96</td><td>2.42</td><td>2.93</td><td>20.58</td><td>16.97</td><td>1,610</td><td>1,327</td><td>493</td><td>407</td></tr>
<tr><td>Male</td><td></td><td></td><td>0.95</td><td>0.97</td><td>2.04</td><td>2.20</td><td>24.39</td><td>22.64</td><td>1,907</td><td>1,771</td><td>585</td><td>543</td></tr>
<tr><td>**Age**</td><td>7.63***</td><td>10.01***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>18 ~ 25 years</td><td></td><td></td><td>0.96</td><td>0.96</td><td>3.27</td><td>3.04</td><td>15.22</td><td>16.35</td><td>1,190</td><td>1,279</td><td>365</td><td>392</td></tr>
<tr><td>26 ~ 35 years</td><td></td><td></td><td rowspan="4">0.94</td><td>0.98</td><td rowspan="4">2.14</td><td>2.17</td><td rowspan="4">23.21</td><td>22.96</td><td rowspan="4">1,815</td><td>1,796</td><td rowspan="4">556</td><td>551</td></tr>
<tr><td>36 ~ 45 years</td><td></td><td></td><td rowspan="3">0.93</td><td rowspan="3">2.75</td><td rowspan="3">18.11</td><td rowspan="3">1,417</td><td rowspan="3">434</td></tr>
<tr><td>46 ~ 55 years</td><td></td><td></td></tr>
<tr><td>≥ 56 years</td><td></td><td></td></tr>
<tr><td>**Income**</td><td>38.83***</td><td>40.69***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>< ¥68,000</td><td></td><td></td><td rowspan="4">0.93</td><td rowspan="3">0.94</td><td rowspan="4">2.54</td><td rowspan="3">3.54</td><td rowspan="4">19.60</td><td rowspan="3">14.08</td><td rowspan="4">1,533</td><td rowspan="3">1,101</td><td rowspan="4">470</td><td rowspan="3">338</td></tr>
<tr><td>¥68,000 ~ ¥98,000</td><td></td><td></td></tr>
<tr><td>¥98,000 ~ ¥137,000</td><td></td><td></td></tr>
<tr><td>¥137,000 ~ ¥239,000</td><td></td><td></td><td rowspan="2">0.96</td><td rowspan="2">1.92</td><td rowspan="2">25.95</td><td rowspan="2">2,030</td><td rowspan="2">622</td></tr>
<tr><td>> ¥239,000</td><td></td><td></td><td>0.91</td><td>1.25</td><td>39.67</td><td>3,103</td><td>951</td></tr>
<tr><td>**Preference**</td><td>20.49***</td><td>30.13***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Economy hotels</td><td></td><td></td><td rowspan="2">0.95</td><td rowspan="2">0.95</td><td rowspan="2">2.60</td><td rowspan="2">2.67</td><td rowspan="2">19.17</td><td rowspan="2">18.61</td><td rowspan="2">1,499</td><td rowspan="2">1,455</td><td rowspan="2">460</td><td rowspan="2">446</td></tr>
<tr><td>Midscale hotels</td><td></td><td></td></tr>
<tr><td>Upscale hotels</td><td></td><td></td><td rowspan="2">0.94</td><td>0.96</td><td rowspan="2">1.89</td><td>1.85</td><td rowspan="2">26.39</td><td>26.90</td><td rowspan="2">2,064</td><td>2,104</td><td rowspan="2">633</td><td>645</td></tr>
<tr><td>B&Bs</td><td></td><td></td><td>0.95</td><td>3.77</td><td>13.21</td><td>1,033</td><td>317</td></tr>
<tr><td>**Risk tolerance**</td><td>19.91***</td><td>54.41***</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Below-average</td><td></td><td></td><td>0.93</td><td>0.96</td><td>2.51</td><td>3.06</td><td>19.83</td><td>16.26</td><td>1,551</td><td>1,271</td><td>476</td><td>390</td></tr>
<tr><td>Above-average</td><td></td><td></td><td>0.97</td><td>0.97</td><td>2.05</td><td>2.16</td><td>24.24</td><td>23.06</td><td>1,896</td><td>1,804</td><td>581</td><td>553</td></tr>
</table>

*** $p < .001$.

Many studies have corroborated the impact of demographic and psychological characteristics on consumers' choices of and demand for hotels and other tourism products (Lee & Hwang, 2011). This study deepens our understanding by showing how these characteristics diversify the demand curves for different hotels. The demand curves for economy and upscale hotels generally showed less heterogeneity among consumers, whereas heterogeneity was greatest for the demand curve of midscale hotels. Consequently, consumers' characteristics affected the valuation of midscale hotels more than they affected the valuations of other hotels, implying that midscale hotels faced more varied market segmentation and therefore needed more diversified marketing strategies than other hotels. The pandemic situation mitigated [amplified] the influence of the sociodemographic factors and consumption preferences on the demand curve for midscale [upscale] hotels.

Combining the results of three hotel types, we recognized that, first, the demand curves of middle-aged and elder adults varied depending on the situation, whereas those of young adults were unresponsive to situational changes. Among the young adults, the group aged 18-25 years [26-35 years] had a substantially elastic [inelastic] demand curve. Studies have identified age as a vital influencer of consumers' normal choices (Tran et al., 2019) and decision-making amid COVID-19 (Foroudi et al., 2021). The present study further highlights the impact of age on the demand curves of consumers in the normal versus pandemic situation. Second, in terms of consumption preferences, frequent customers to a specific hotel type tended to demonstrate relatively inelastic demand and high essential values, which were resilient to the pandemic situation. This is consistent with findings regarding customer loyalty (Blinder et al., 1998). Third, people who preferred B&Bs generally attached low [high] value to midscale [upscale] hotels, implying a potential substitutive [non-substitutive] interaction, as suggested by Guttentag and Smith (2017). However, this valuation pattern was reversed in the pandemic situation. Fourth, risk tolerance differentiated the demand curves to a greater extent in the pandemic situation, aligning with many studies that have indicated that risk tolerance significantly influenced consumer demand amid COVID-19 (Landry et al., 2021).

Besides, several demand patterns remained consistent across hotel types and consumption situations. First, women tended to have more elastic demand curves and lower essential values than men. This difference in demand may reflect differences in decision-making between the genders. In general, women have been shown to be more concerned than men about budget, time, uncertainty and the consequences of decisions, whereas men focus more on motivation and goals

(Cannon-Bowers et al., 1996). In addition, women tend to perceive higher risks in various circumstances than men (Finucane et al., 2000), thereby displaying more negative reactions to cost increases. Women's higher price sensitivity compared with men's has been documented in other economic domains, such as alcohol consumption (Saffer & Dave, 2006). Second, we found that the higher the income or the risk-tolerance level, the more inelastic the demand curves were. The effect of income on price elasticity has been found to be consistently significant in various consumption settings (Canina & Carvell, 2005), as consumers with higher incomes have a greater spending capacity at all prices. Risk-tolerant individuals have a propensity to make riskier decisions than risk-averse individuals (Williams et al., 2022) and therefore generally exhibit less concern about potential loss and disappointment.

3.5 Conclusions

This study developed a demand model based on a behavioral economics approach to analyze the heterogeneity of demand curves based on the consumption situation and individual differences across three hotel types. For midscale [upscale] hotels, the pandemic situation slowed [accelerated] the rate of elasticity increase along the demand curve, making demand more inelastic [elastic] at all price points and indicating a higher [lower] valuation from consumers compared with a normal situation. However, this change in the consumption situation exerted no significant influence on the demand curve for economy hotels. Individual differences affected the shape of the demand curve and differentiated various consumer segments, which are relatively diversified [undiversified] for midscale [economy and upscale] hotels. The pandemic situation mitigated [amplified] the influence of individual differences on the demand curve for midscale [upscale] hotels, but it amplified the influence of risk tolerance under all conditions.

This is one of the first empirical studies to apply the demand framework of "behavioral" behavioral economics, including a novel demand model and the hypothetical purchase task technique, to explore the heterogeneity of hotel demand curves across consumers and contexts. The study fills three main research gaps in current hospitality and tourism demand studies: 1) modeling the complete demand curve over a wide price range to map the detailed shape of the demand curve; 2) parameterizing the dynamics of elasticity along the demand curve and interpreting them conceptually and empirically; and 3) increasing the flexibility of econometric demand modeling by extending it to the disaggregate level to discover and compare the demand curves of consumer segments and individual businesses in different consumption situations.

From a managerial perspective, the findings provide insights into business strategies. First, understanding complete demand curves and the dynamics of elasticity allows managers to establish the linkages between price, demand and revenue. The optimal pricing point derived from the demand side maximizes revenue and is more relevant than the long-term market equilibrium price in informing managers in individual enterprises of the pricing decisions. Second, insights into the influence of individual differences on demand curves can support customized marketing strategies across consumer groups. Third, the observed shifts in the demand curves resulting from the pandemic situation have critical implications for the crisis management strategies employed by hotels to proactively adapt and safeguard against fluctuations in demand during periods of crisis. Since crises and economic downturns distort standard market patterns and therefore shift household economic structure (Craig & Churchill, 2021; Smeral, 2018), it is critical for businesses to focus on their essential (ideal) customers who exhibit relatively inelastic demand and high essential values that are insensitive to external disruptions and to implement appropriate price adjustments (i.e., lowering price if the demand curve becomes more elastic and the essential value becomes smaller; vice versa) to achieve higher revenue. Specific managerial advice for each hotel type is provided below.

- *Economy hotels* are a necessity in the realm of lodging products, as they meet consumers' most basic needs and therefore demonstrate a relatively consistent market valuation and a stable demand curve, which was unaffected by the pandemic situation. It is therefore recommended that economy hotels maintain their status-quo pricing strategies during a health crisis. Their essential customers are middle-income people aged 26 years or older. As the demand curves for economy hotels are less heterogeneous across consumer segments than those of other hotels, economy hotels have little room to customize pricing or marketing. Nevertheless, as the pandemic has led consumers to prioritize epidemic prevention measures and hygiene when choosing an accommodation, and as this new emphasis is likely to persist in the aftermath of the pandemic, an economy hotel can differentiate itself from its competitors by enhancing its professional and managerial abilities to address these issues and strengthening its brand image and reputation.

- *Midscale hotels* must manage the most complicated array of market segments, as the valuation of midscale hotels fluctuates among different consumers. The essential customers in a normal situation are middle-aged and high-income individuals. The pandemic situation substantially altered the demand curve of midscale hotels, making the demand more inelastic at all prices. Thus, midscale hotels could consider increasing their room rates to generate increased revenue amid a health crisis. Special attention should be paid to young adults, senior adults, middle-income people, and people who normally stay in economy hotels and B&Bs, as they markedly raised their valuations of midscale hotels during the pandemic. Because of the differentiated products and services offered, each midscale hotel has the potential to distinguish itself from its competitors by developing unique selling points and branding strategies that allow it to charge premium-level prices.
- *Upscale hotels* have a clear market image as a luxury lodging product and a demand curve that is relatively unaffected by consumers' characteristics. The essential customers are high-income earners aged 26 years or above with an accommodation preference for upscale hotels. A differentiated pricing strategy is favorable for these hotels given the wide gap in optimal prices among different consumer groups. The pandemic situation increased the overall elasticity of the demand curve for upscale hotels, with consumers showing varying reactions to this environmental change. Therefore, upscale hotels should be cautious about increasing their room rates during a health crisis. The status quo can be maintained for young adults, and there is an opportunity to improve the hotels' market penetration by targeting moderately high-income people. Frequent customers are an asset in both normal and pandemic circumstances, so earning and keeping frequent customers should be at the core of upscale hotels' business strategies.

Furthermore, individual hotels can use the findings of this study to develop customized and effective pricing strategies according to their market positions. A hotel can match its customer composition to the demand curves of the corresponding consumer segments to obtain its own essential value(s) and optimal pricing point(s). In this way, the hotel can establish its own demand curve and business strategies specific to its situation.

Despite the above implications, this study has some limitations. First, the demand curve analyses assumed stable market supply, so the results may be altered when considering business startups or shutdowns. This is worth exploring in future studies. Second, hypothetical purchase task measures stated behavior and may have limited predictive validity for actual behavior, a challenge faced by all laboratory experiments. Meanwhile, measuring demand in a probability format and assuming a monopolistic market in the experimental design lead to higher measures of behavioral economic value and more inelastic demand curves. Although the hypothetical purchase task method is the best option for this study considering the lack of secondary data, future studies are encouraged to fit eligible secondary data series, where available, to model actual consumer demand at the disaggregate level. Third, this study is situated in a single market. Future research should be extended to other geographical/cultural regions to deliver more generalizable conclusions and to explore the differences across markets. Fourth, online surveys may introduce sample selection bias to a certain extent. While this study demonstrates the novel methodology for modeling disaggregate demand curves and detecting heterogeneous demand curves across consumers and contexts, studies aiming to construct and interpret the demand curve of a particular market segment are recommended to work on a sufficiently representative sample pool.

Chapter 4 Substitution Between Sharing Accommodation and Hotels: A Behavioral Economic Demand Curve Analysis

This chapter presents the third study of this thesis, an empirical research paper published in the *Annals of Tourism Research* (Lin et al., 2024). Section 4.1 provides an overall introduction to the research question and aim. Section 4.2 reviews previous research on the relationship between sharing accommodation and hotels, focusing on the quantification of substitution. Section 4.3 details the methods used for data collection and analysis. Section 4.4 presents the model results. Finally, Section 4.5 discusses the key findings, explaining the research implications and acknowledging limitations.

4.0 Abstract

Researchers have confirmed the substitution of sharing accommodation for hotels. The existing assessments of the substitution have primarily focused on the inverse relationship between sharing accommodation supply and hotel performance, with a lack of examination based on demand curve analysis. This study utilizes behavioral economic demand models to construct alone-price/own-price demand curves for hotels and cross-price demand curves for sharing accommodation to quantify the substitutive relationship between sharing accommodation and different hotel types. Furthermore, we explore the variations in this substitutive relationship by travel companion and customer group. The analysis is dual-directional, including both the substitutability of sharing accommodation for hotels and the reverse relationship. The findings inform market competition strategies for hotels and sharing accommodation.

4.1 Introduction

Sharing accommodation has emerged as a new alternative to conventional lodging establishments. Industry managers and researchers have debated its impact, with some viewing it as a disruptive threat to hotels (Guttentag & Smith, 2017) while others seeing it as a supplement to the lodging market, offering benefits to the tourism industry and presenting a mix of both opportunities and challenges (Fang et al., 2016). Nevertheless, most researchers acknowledge the presence of a substitutive relationship between sharing accommodation and hotels given their similar functions and purposes. Moreover, sharing accommodation has been observed to compete with different hotel types to varying degrees (Zheng et al., 2023).

Prior research has predominantly evaluated the substitution of sharing accommodation for hotels by examining the adverse impacts of sharing accommodation supply on hotels' business performance (Dogru et al., 2020) with mixed conclusions being drawn. Nevertheless, scant research has looked into the substitutive relationship between these two related goods from the perspective of demand curves. In microeconomics, the substitutive relationship is characterized by an increasing demand for the substitute good as the price of the primary good rises, manifested by an upward-sloping cross-price demand curve. Therefore, there is a need for research investigating the substitutive relationship between sharing accommodation and different hotel types based on the analysis of demand curves and cross-price elasticities. Meanwhile, it would be more comprehensive to study the substitutive relationship from both directions, as the substitutability of good A for good B may not necessarily be symmetric to the substitutability of good B for good A (Nicholson & Snyder, 2017). The existing research has primarily focused on the impact of sharing accommodation on hotels while to certain extent neglecting how hotels may substitute for sharing accommodation.

In most tourism demand studies that have explored substitution based on demand curves, the substitutability of a particular good for another has been quantified through the cross-price elasticity coefficient within an econometric demand model (Song et al., 2009). However, a single coefficient is insufficient to describe the price-demand relationship, since it is either derived from one single price point or assumed to remain constant with price. Relative to traditional econometric demand models that estimate constant own-price and cross-price elasticity coefficients, the construction of complete own-price and cross-price demand curves, which account for varying elasticities, provides a more thorough understanding of demand's response to price changes. In this regard, behavioral economic demand models, featuring exponential functional forms that parameterize the change rate of elasticity along complete demand curves, offer significant advantages over traditional econometric demand models in describing demand and elasticities.

This methodology enables mathematical and visual comparisons of how the shape of a demand curve changes under different scenarios.

In view of the above, this study aims to examine the substitutive relationship between sharing accommodation and different hotel types. This examination involves modeling the alone-price and own-price demand curves for hotels, along with the cross-price demand curves for sharing accommodation in relation to hotel prices, to quantify the substitutability of one for the other and providing insights into how the substitutive relationship between sharing accommodation and hotels varies across different hotel types. This study also investigates whether the substitutive relationship differs between customers with different travel companions and how it is influenced by customer characteristics.

This study is the first attempt to evaluate the dual-directional substitutive relationship between sharing accommodation and different hotel types based on demand curve analysis. In contrast to previous demand modeling research, this study employs behavioral economic demand models, among which the cross-price demand model and the multivariate own-price demand model are used in tourism research for the first time. These models serve as an innovative approach to conducting in-depth examinations of the substitution with respect to travel companions and customer groups. A unique contribution of this study lies in its provision of a standardized quantitative framework for investigating the substitutive relationship between sharing accommodation and hotels as well as its variations across customer segments and contexts.

4.2 Literature Review

4.2.1 Sharing accommodation and hotels

Since the advent of sharing accommodation, researchers have delved into customer preferences for sharing accommodation versus hotels to understand how sharing accommodation attracts customers and influences market segmentation within the lodging industry. Prior studies have indicated that customers tend to favor sharing accommodation over hotels when looking for a relaxed vacation close to home (Lee et al., 2003) or traveling to domestic destinations (Ye et al., 2023) and when traveling with friends for extended periods (Poon & Huang, 2017). Regarding sociodemographic characteristics, males, younger individuals, experienced tourists and well-educated people are more inclined to choose to share accommodation over hotels compared to their counterparts (Jones & Guan, 2011; Miciak et al., 2001). As for personality attributes, people with higher degrees of allocentrism (Poon & Huang, 2017) and innovativeness (Wang & Jeong, 2018) tend to prefer sharing accommodation to hotels, whereas neuroticism shows a negative effect on customer preference to sharing accommodation (Ye et al., 2023). Given that customer preferences vary based on travel arrangements and personal traits, the competition between sharing accommodation and hotels is likely to differ across various customer segments.

Customers' motivations for choosing sharing accommodation are rooted in the private atmosphere, personal service, social interaction, enjoyment, home benefits and value for money (Miciak et al., 2001; So et al., 2018; Tussyadiah, 2015; Zane, 1997). It is widely recognized that sharing accommodation is consumed as an alternative to traditional hotels and is considered a disruptive innovation within the hotel market (Guttentag & Smith, 2017). Most studies have concluded that there exists an imperfect substitution between sharing accommodation and hotels. However, findings regarding how their competition fluctuates across various market segments are still debated.

One prevailing perspective suggests that sharing accommodation competes with hotels mainly on price and poses a particular threat to the market share of lower-end hotels and those catering to leisure travelers (Fang et al., 2016; Zervas et al., 2017). Hotel managers generally regard sharing accommodation as a significant competitor for small to midscale hotels but not for major hotel brands (Varma et al., 2016). Dogru et al. (2019) substantiated this argument by demonstrating that the market performance of economy hotels was most affected by the increasing sharing accommodation supply, although midscale hotels and luxury hotels were also negatively impacted. However, some researchers argue that sharing accommodation competes more directly with midscale hotels than with economy ones (Oskam & Boswijk, 2016). Guttentag and Smith (2017) further specified that customers commonly use sharing accommodation as a substitute for midscale hotels, followed by economy hotels and upscale hotels.

Another research perspective indicates a more adverse impact on the sales performance of luxury hotels due to sharing accommodation supply, compared to upper upscale hotels (Blal et al., 2018). In contrast to the assertion of a purely substitutive relationship between sharing accommodation and hotels, Ginindza and Tichaawa (2019) observed a positive correlation between the demand for sharing accommodation and hotels, suggesting a potential complementary relationship. Moreover, Henten and Windekilde (2016) proposed a scenario in which complementation and substitution exist on the supply and demand sides, respectively.

The mixed findings regarding the substitutive relationship between sharing accommodation and hotels can be attributed to different empirical contexts in research, varying types of listings and, most importantly, different measures of the substitution employed across studies. Previous research examined the substitution by validating whether sharing accommodation supply negatively impacted hotel performance using various metrics, such as revenue per available room, average daily rate and occupancy rate (Dogru et al., 2020; Sainaghi & Baggio, 2020). It has been subsequently demonstrated that the adverse impact of sharing accommodation supply on hotel revenue is primarily driven by reductions in hotel prices rather than reductions in hotel demand, although economy hotels experience declines in both price and demand (Dogru et al., 2022). This is more likely indicative of the homogeneity between sharing accommodation and hotels as lodging products than direct evidence of a substitutive relationship. In other words, the availability of sharing accommodation increases the overall market supply, leading to a lower market equilibrium price.

Instead of measuring the negative correlation between the supply of one product and the revenue of another, in microeconomics, a substitutive relationship between two related goods is defined as a positive correlation between the price of the primary good and the demand for the alternative good, as indicated by an upward-sloping cross-price demand curve. This aspect has not been thoroughly investigated to quantify the degree of substitution between sharing accommodation and different hotel types.

4.2.2 Measuring the substitution

An own-price demand curve is a graphical representation depicting the correlation between the price of a good and the demand for that good at different price points, whereas a cross-price demand curve illustrates how the demand for one good changes with variations in the price of a related good. The configuration of the cross-price demand curve and the magnitude of the cross-price elasticity help determine the nature of the relationship between the two goods – whether they are complements (negative cross-price elasticity), substitutes (positive cross-price elasticity) or unrelated goods (zero cross-price elasticity). A steeper cross-price demand curve means a stronger complementarity/substitutability of one good for the other. It is worth noting that the substitutability can be asymmetric, especially when the two goods are not perfect substitutes (Nicholson & Snyder, 2017).

A demand model, upon which the demand curve is based, is a mathematical representation of the relationship between demand and its determinants. Demand models have been widely applied in tourism and hospitality research with a specific emphasis on economic aspects, including demand forecasting (Song et al., 2019), determinant identification (Martins et al., 2017) and elasticity estimation (Peng et al., 2015). In the context of lodging products, prior research has primarily focused on own-price elasticities, demonstrating variations in these elasticities based on factors such as season, hotel type and hotel brand (Vives et al., 2019). Cross-price elasticity estimation has predominantly relied on destination competition (Song, Lin, et al., 2011), with only a limited number of recent studies exploring the substitutive relationship between hotels and other accommodation types (Boto-García & Mayor, 2022).

To recap, the assessment of the substitution of sharing accommodation for different hotel types has centered on the adverse effect of sharing accommodation supply on hotel performance and the resulting increases in hotel own-price elasticities (Chen et al., 2022). There is a dearth of research utilizing the cross-price demand curve for sharing accommodation with hotel prices to establish a direct measurement of the substitutability of sharing accommodation for hotels. Conversely, it is also worthwhile to investigate the substitutability of hotels for sharing accommodation to validate the symmetry of the substitutive relationship between the two products.

In traditional econometric demand models used in most tourism and hospitality studies, demand elasticity is normally estimated as a constant coefficient, which may pose certain issues. On the one hand, the estimation of constant elasticity coefficients is partly due to the prevalent use of constant-elasticity demand models in a double-log functional form, driven by the simplicity of model estimation and coefficient interpretation (Song et al., 2009). However, own-price elasticity is expected to vary along most demand curves, typically increasing with price. A demand curve with constant elasticity represents a special case where the demand curve follows a power functional form (Perloff, 2018). The same applies to cross-price demand curves and cross-price elasticities. On the other hand, even when dynamic-elasticity demand models are used, researchers frequently estimate elasticity coefficients at the average price for easy interpretation, resulting in a single coefficient. This leads to a significant loss of information at all prices other than the transient average. Furthermore, comprehending the dynamics of elasticity holds substantial economic significance and is particularly crucial for pricing strategies (Alrawabdeh, 2022). Describing the relationship between price, demand and revenue hinges on constructing a complete demand curve with specified elasticity coefficients at all price levels, which enables the identification of the optimal pricing point that maximizes revenue.

Considering the above, a novel demand model is essential to parameterize the dynamics of elasticity and construct complete demand curves to comprehensively describe the relationship among relevant economic variables. This study therefore employs behavioral economic demand models to address the issues associated with constant elasticity coefficients and conducts a thorough analysis of the substitutive relationship between sharing accommodation and different hotel types.

4.2.3 Behavioral economic demand models

Behavioral economic demand models originate from the field of "behavioral" behavioral economics, which integrates economic principles into operant psychology to explain the reinforcement of consumption/acquisition behavior by a certain good (Hursh & Roma, 2013). This is distinct from what most researchers in the social sciences would typically recognize as behavioral economics (the "cognitive" behavioral economics), which instead incorporates cognitive psychology into economics to explore the disparities between humans' actual decisions and the rational decisions presumed in economic theory. In this study, we focus on "behavioral" behavioral economics and its associated demand models to analyze the substitution between sharing accommodation and hotels. This approach is favored for its superior attributes over traditional econometric demand models in specifying the dynamics of elasticity and depicting complete demand curves.

In "behavioral" behavioral economics, a demand curve illustrates the degree of resource allocation that an individual would allocate to access a good as its cost increases (Kaplan et al., 2018). Unlike econometricians who often regress demand at a limited range of market price points, behavioral scholars scrutinize the complete demand curve, encompassing the range from zero price, where demand is anticipated to peak (termed as demand intensity Q_0), to the price at which demand dwindles to zero (known as the breakpoint *BP*). The concept of demand elasticity is reflective of the reinforcing efficacy of a good on an individual's consumption behavior. By constructing complete demand curves, researchers have unveiled the dynamics of elasticity, demonstrating that own-price elasticity increases with price and transitions from inelastic to elastic regions. The demand curve, drawn on the logarithmic coordinates, takes the form of a downward-sloping concave curve rather than the linear decrease estimated by double-log demand models. Additionally, the shape of the demand curve entails an inverted U-shaped total revenue curve, reaching its apex at the price of unit elasticity (called the optimal pricing point P_{max}). The maximum revenue point is denoted as O_{max}.

As the dynamics of elasticity demonstrate a systematic increase with price, an ideal demand model should focus on defining the change rate of elasticity. To this end, Hursh and Silberberg (2008) introduced the initial behavioral economic demand model, the exponential model, which incorporates a parameter α into the exponential term to specify the increasing rate of own-price elasticity with price. The concept of essential value, inversely linked to parameter α, was devised to quantify a good's efficacy as a reinforcer to strengthen or sustain an individual's consumption despite price increases. A large parameter α indicates a higher increasing rate of elasticity with price, implying that the demand curve decays more rapidly. Thus, the reinforcing efficacy of the good is relatively weak in maintaining consumption levels against rising costs, signifying a lower essential value or lower consumer valuation. The exponential model has been validated as superior to the widely applied double-log, semi-log and linear demand functions for explaining secondary demand data (Yan et al., 2012). One of the principal advantages of essential value over point elasticity in elucidating price-demand relationships lies in its capacity to extend elasticity insights beyond a single price point to embrace the entire price spectrum. Furthermore, it offers ease of interpretation and comparability across various products and consumers.

The "behavioral" behavioral economics explores the interplay between related goods using cross-price demand curves. A positive/negative slope signifies substitution/complementation, and the degree of substitution/complementation hinges on the steepness of the slope. Moreover, the relative shift between the alone-price demand curve (assuming the related good is unavailable) and the own-price demand curve (assuming the related good is available) offers additional evidence of the relationship. Specifically, when a substitution/complementation effect stands, the presence of the substitute/complement will depress/enhance the demand for the primary good and weaken/strengthen its reinforcing efficacy or resistance to price increases. This is manifested as a greater/smaller parameter α in the own-price demand curve compared to the alone-price demand curve. The behavioral economic framework has proven highly effective in behavioral science for examining the substitutive/complementary relationships between various products, such as e-cigarettes and conventional cigarettes (Snider et al., 2017), cannabis and cigarettes (Cooper et al., 2023), and alcohol and cannabis (Pereira-Morales & Eslava-Schmalbach, 2022).

A recent development involves the creation of a multivariate behavioral economic demand model, which incorporates both own-price and cross-price variables to explain demand. In this model, parameter α remains responsible for specifying the change rate of own-price elasticity, while parameter β is introduced to define the change rate of cross-price elasticity (Hursh & Schwartz, 2023). The model provides a more comprehensive description of demand compared to the early univariate behavioral economic demand models by developing a three-dimensional demand surface rather than two-dimensional demand curves. It can be regarded as a successful amalgamation of the advantages of traditional econometric demand models in estimating coefficients for multiple demand determinants and the benefits of behavioral economic demand models in parameterizing the dynamics of elasticity along a complete demand curve. The application of this multivariate model in empirical studies has been somewhat limited, primarily centered on assessing temporal discounting in the context of substance value (Rzeszutek et al., 2023). To date, it has not been extensively tested for fitting demand data. Furthermore, the application of behavioral economic demand models in tourism and hospitality research remains scarce, as the “behavioral” behavioral economics is still a relatively new field for tourism researchers, introduced for the first time by Song and Lin (2023).

To bridge the research gaps of examining the substitutive relationship between sharing accommodation and different hotel types through the lens of demand curves and delineating complete demand curves that reveal the dynamics of elasticity, this study evaluates the dual-directional substitution between sharing accommodation and hotels using behavioral economic demand models. Alone-price, own-price and cross-price demand curves are constructed with comparable parameters to quantify the degrees of substitution.

4.3 Method

This study was conducted within the US lodging market and aimed to investigate the substitutive relationship between sharing accommodation and three main hotel types – economy, midscale and upscale hotels. Considering the multifaceted factors influencing customer preferences between sharing accommodation and hotels as discussed in Section 4.2.1, one of the most noteworthy factors is the presence of travel companions (Poon & Huang, 2017). It not only shapes customers' travel activities but also their accommodation needs. Regarding the room types of sharing accommodation, for instance, when a customer travels alone or with a partner, a private room in a shared home is often suitable, whereas groups of friends or family members traveling together tend to prefer an entire home over multiple independent rooms. Therefore, this study sought to examine whether the presence of travel companions would influence the substitutive relationship between sharing accommodation and hotels.

The research adopted a 3 (*hotel type*: economy vs. midscale vs. upscale) × 2 (*travel companions*: travel alone vs. travel with friends) between-subjects experimental design. The categorization of hotels aligned with the segments used in the North America Hotel Guest Satisfaction Index Study conducted by J.D. Power (2023). For the purposes of this study, "traveling alone" and "traveling with friends" corresponded to different room types of sharing accommodation – staying in a private room within a shared home for the former and booking an entire home for the latter. To control the influence of potential confounding variables on demand, the travel scenario was designed as a one-week domestic leisure trip to an urban city.

4.3.1 Hypothetical purchase task

As a typical behavioral economic gauge of demand (Kaplan et al., 2018), the hypothetical purchase task was employed to collect individual demand data by presenting participants with escalating prices ranging from zero to the breakpoint price. The hypothetical purchase task was structured into distinct versions of questionnaires, each tailored for one of the six experimental groups. Participants were randomly assigned to these groups and began by viewing representative images of their assigned hotel type and sharing accommodation, along with a travel scenario description and basic assumptions. Each questionnaire comprised two sequential scenarios. The first scenario assumed that sharing accommodation was unavailable, allowing for the measurement of alone-price demand for hotels. The second scenario considered sharing accommodation as an available option, facilitating the measurement of own-price demand for hotels and cross-price demand for sharing accommodation.

In each scenario, participants were asked to report their demand – purchase likelihood as proposed by Roma et al. (2016) and validated by numerous empirical studies (Brown et al., 2022) – for the certain hotel/sharing accommodation at various hotel/sharing accommodation prices. The notion of demand hereafter represents demand probability. To strike a balance between the precision of demand curves and the participants' workload, the questionnaire included seven price points for hotels and five price points for sharing accommodation. This resulted in seven demand questions under the alone-price scenario and 35 demand questions under the own-price/cross-price scenario. In all cases, the price started from zero, and the average market price was put as the median of the price series. The progression of prices followed a generally even logarithmic pattern. The price series for each hotel type concluded at an estimated breakpoint price, set at five times the average market price, based on findings from pilot tests. The pilot results also indicated that the maximum price for sharing accommodation should be set at two times the average market price, beyond which the substitutability of sharing accommodation for hotels diminished. See the Appendix B for the complete questionnaire.

4.3.2 Participants

Participants were recruited from the US via Amazon Mechanical Turk and received a compensation of $1.00 for each successfully completed "human intelligence task". We collected a total of 675 valid responses. The final participant pool comprised 54.5% females and 45.5% males. Participants' ages ranged from 18 to 77 years, with a mean of 40 years. Additional details regarding age, income, education and employment can be found in Table 4.1.

Table 4.1 Participant demographics.

	Frequency	Percentage
Gender		
Female	368	54.5
Male	307	45.5
Age		
18 ~ 25 years	96	14.2
26 ~ 35 years	202	29.9
36 ~ 45 years	148	21.9
46 ~ 55 years	120	17.8
≥ 56 years	109	16.1
Annual household income		
< $40,000	161	23.9
$40,000 ~ $79,999	206	30.5
$80,000 ~ $119,999	145	21.5
$120,000 ~ $159,999	82	12.1
≥ $160,000	81	12.0
Highest level of education		
High school or lower	80	11.8
Technical/vocational training	69	10.2
Bachelor's degree	365	54.1
Postgraduate degree	161	23.9
Employment status		
Employed full-time	485	71.9
Employed part-time	57	8.4
Self-employed	45	6.7
Unemployed	23	3.4
Not in the labor force	65	9.6

4.3.3 Data analysis

For each hotel type, we constructed both alone-price and own-price demand curves, as well as the cross-price demand curve for sharing accommodation in relation to the hotel price. As per Hursh and Silberberg (2008), the alone-price demand model is expressed as follows:

$$log_{10}(Q) = log_{10}(Q_0) + k(e^{-\alpha P} - 1), \tag{4.1}$$

where Q is hotel demand, P is hotel price, Q_0 is the demand intensity of hotel (the demand at zero hotel price), k is a predetermined span parameter to restrict the range of logarithmic demand, and parameter α is the estimated change rate of elasticity. Since we measured demand in probability, the span of demand (parameter k) was always equal to $log_{10}(Q_0)$. This model can thus be simplified as follows:

$$log_{10}(Q) = log_{10}(Q_0)e^{-\alpha P}, \tag{4.2}$$

which was used to fit the alone-price demand curves for hotels. Q and P are input variables, whereas Q_0 and α are estimated coefficients.

The cross-price demand curves for sharing accommodation, modeled with a sharing accommodation price equal to the market average ($90), were fitted following the approach of Hursh and Roma (2013):

$$log_{10}(Q) = log_{10}(Q_0) + Ie^{-\beta P_S}, \tag{4.3}$$

where Q is sharing accommodation demand, P_S is hotel price, Q_0 is the demand intensity of sharing accommodation (the demand at infinite hotel price), I is called the interaction constant to reflect the relationship between two related goods (I > 0: complementary, I < 0: substitutive), and parameter β specifies the change rate of cross-price elasticity. The higher the β, the stronger the substitutability of sharing accommodation for hotels. In Equation 4.3, Q and P_S are input variables, whereas Q_0, I and β are estimated coefficients.

To account for sharing accommodation's participation in market competition, the own-price demand curves for hotels were fitted using a multivariate functional form that considered both hotel price and sharing accommodation price. Adapted from Hursh and Schwartz (2023), the demand model is defined as:

$$log_{10}(Q) = log_{10}(Q_0)e^{-\alpha P} + Ie^{-\beta P_S}, \tag{4.4}$$

where Q, Q_0 and P are the hotel demand, hotel demand intensity (the demand at zero hotel price and infinite sharing accommodation price) and hotel price respectively, P_S is sharing accommodation price, I is the interaction constant, parameter α is the change rate of the hotel own-price elasticity, and parameter β is the change rate of the hotel cross-price elasticity. A higher β means a stronger substitutability of hotels for sharing accommodation. Here, Q, P and P_S are input variables, whereas Q_0, I, α and β are estimated coefficients.

In summary, the substitutability of sharing accommodation for a particular hotel type could be identified by observing a more elastic hotel own-price demand curve compared to its alone-price demand curve, along with the parameter β on the cross-price demand curve for sharing accommodation. Conversely, the substitutability of a certain hotel type for sharing accommodation would be reflected by the parameter β on the multivariate own-price demand curve for hotels. Since the demand models necessitated log transformation, zero values in the demand data were replaced with a value of 1 (%).

The essential value (*EV*) was calculated as the reciprocal of parameter α. A larger essential value indicates a flatter demand curve and a greater insensitivity to price increases, suggesting a higher valuation of the hotels. Based on nonlinear least squares, an individual demand curve was fitted using pooled data of the participants from one segmented group and was regarded as the representative demand curve of this group of individuals (Kaplan, 2018). Before modeling, extra sum-of-squares F-tests were conducted to determine whether the groups under investigation exhibited different demand curves, thus confirming the segmentation structure. The null hypothesis posited that the tested groups shared the same parameter α; its rejection would indicate the need for separate estimations of the demand curve.

4.4 Results

4.4.1 Manipulation checks

After reading the scenario description, participants answered two manipulation check questions to validate the manipulation of hotel types and travel companions, respectively, on a 7-point Likert scale. For hotel types, participants assessed the cost of staying in economy/midscale/upscale hotels. And for travel companions, participants rated the extent to which they agreed with the statement "In this trip, I make decisions on my travel activities alone" if they travel as described in the given scenario. The manipulation checks were successful as intended. Participants perceived significantly different costs associated with staying in the three hotel types ($F = 161.64$, $p = 0.00$), with upscale hotels having the highest mean cost rating ($M = 5.66$), followed by midscale hotels ($M = 4.51$) and economy hotels ($M = 3.73$). Furthermore, participants under the "travel alone" scenario ($M = 6.23$) reported significantly higher agreement with the statement that they made decisions on travel activities alone, compared to participants under the "travel with friends" scenario ($M = 3.39$), as indicated by a t-test ($t = 24.11$, $p = 0.00$).

4.4.2 Substitutive relationship between sharing accommodation and hotels

The F-tests confirmed that economy, midscale and upscale hotels exhibited significantly different alone-price demand curves ($F = 157.19$, $p = 0.00$) as well as own-price demand curves ($F = 263.78$, $p = 0.00$). For each hotel type, its alone-price demand curve remained unaffected by travel companions (economy hotels: $F = 2.16$, $p = 0.14$; midscale hotels: $F = 1.39$, $p = 0.24$; upscale hotels: $F = 0.01$, $p = 0.93$). However, the own-price demand curves showed significant differences between traveling alone and traveling with friends (economy: $F = 120.27$, $p = 0.00$; midscale: $F = 58.46$, $p = 0.00$; upscale: $F = 86.11$, $p = 0.00$). This suggests that the competition introduced by sharing accommodation in the lodging market, especially the offered home benefits for group travelers, made travel companions a significant factor in hotel demand.

Figures 4.1 to 4.3 display the alone-price demand curve and own-price demand curve for each hotel type, together with the cross-price demand curve for sharing accommodation with hotel price, all on the logarithmic coordinates. In each figure, a dotted line marks the point of unit elasticity on the demand curve of the same color, denoting the optimal pricing point P_{max}. It is worth noting that the presented demand curves are different from the common demand curves on microeconomics books, since the price is plotted on the x-axis and the demand is plotted on the y-axis. This is to more intuitively describe the functional relationship between price as an independent variable and demand as a dependent variable so as to better showcase how the elasticity (the slope of the curve) increases with price along the demand curve.

Tables 4.2 to 4.4 provide the model results, including the estimated parameters and the indifference price of the hotels where the demand for hotels matches the demand for sharing accommodation. If the hotel price goes beyond its indifference price, consumers' demand for sharing accommodation would exceed their demand for that hotel type; vice versa. The Appendix C presents a comparison between the behavioral economic demand model and the double-log demand model that has been widely applied in econometric demand modeling practices, demonstrating a better goodness-of-fit and more adequate information and implications that the behavioral economic demand model can provide.

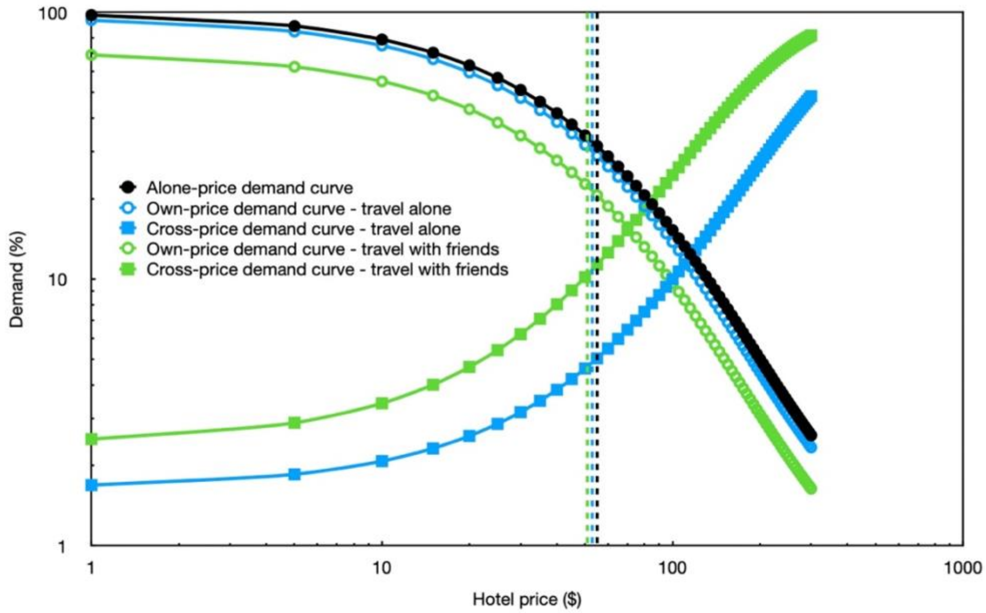


Figure 4.1 Demand curves for economy hotels.

Sharing accommodation had a notable substitutability for economy hotels. The entire demand curve for economy hotels exhibited increased elasticity with the entry of sharing accommodation into the lodging market, resulting in a lower essential value of economy hotels and a reduced optimal pricing point. The increasing cross-price demand curve for sharing accommodation, specified by the negative parameter I, further confirmed that sharing accommodation served as a substitute for economy hotels. Compared to the scenario of traveling alone, the substitutability of sharing accommodation for economy hotels considerably increased when traveling with friends, as evidenced by a larger parameter β on the cross-price demand curve for sharing accommodation in the latter case. Economy hotels were deemed substitutes for sharing accommodation as well, and their substitutability for sharing accommodation decreased when traveling with friends compared to traveling alone.

Table 4.2 Model results: economy hotels.

	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)	Indifference price ($)
Alone-price demand curve (N = 222)	100^{***}	5.25^{***}			0.60	191	55	17	
Travel alone (N = 111)									112
Own-price demand curve	100^{***}	5.47^{***}	35.33^{***}	-0.44^{***}	0.56	183	53	16	
Cross-price demand curve	100^{*}		5.78^{***}	-1.78^{***}	0.31				
Travel with friends (N = 111)									71
Own-price demand curve	100^{***}	5.69^{***}	18.58^{***}	-0.79^{***}	0.49	176	51	11	
Cross-price demand curve	100^{***}		9.74^{***}	-1.62^{***}	0.32				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

EV: Inverse of the elasticity (decay rate) of demand curve; positively correlated with consumers' valuation of the good. P_{max}: Point of unit elasticity; the price where the expected revenue per capita maximizes. O_{max}: Maximum expected revenue per capita.

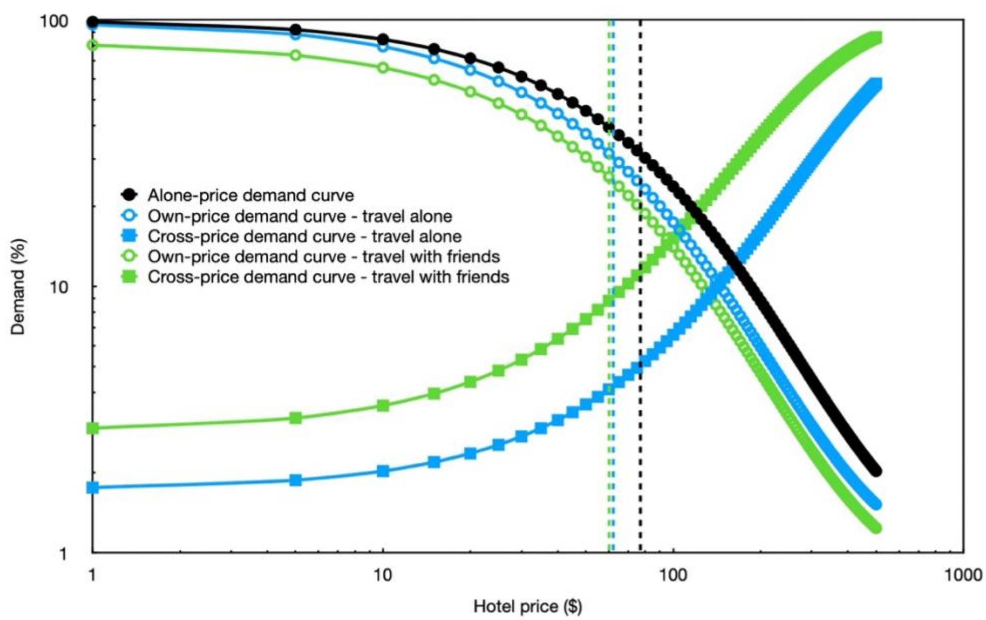


Figure 4.2 Demand curves for midscale hotels.

The negative interaction constants indicated that sharing accommodation and midscale hotels served as substitutes for each other. The entry of sharing accommodation made the entire demand curve for midscale hotels become more elastic, characterized by a higher increasing rate of elasticity, lower essential value and a smaller optimal price. This influence was more pronounced on midscale hotels than on economy hotels. The substitutability of sharing accommodation [midscale hotels] for midscale hotels [sharing accommodation] increased [decreased] when the scenario shifted from traveling alone to traveling with friends.

Table 4.3 Model results: midscale hotels.

	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)	Indifference price ($)
Alone-price demand curve (N = 228)	100^{***}	3.75^{***}			0.64	267	77	24	
Travel alone (N = 116)									144
Own-price demand curve	100^{***}	4.71^{***}	41.22^{**}	-0.34^{***}	0.62	212	62	19	
Cross-price demand curve	100^{**}		4.00^{***}	-1.76^{***}	0.29				
Travel with friends (N = 112)									97
Own-price demand curve	100^{***}	4.84^{***}	21.15^{***}	-0.57^{***}	0.55	207	60	15	
Cross-price demand curve	100^{***}		6.34^{***}	-1.54^{***}	0.27				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

EV: Inverse of the elasticity (decay rate) of demand curve; positively correlated with consumers' valuation of the good. P_{max}: Point of unit elasticity; the price where the expected revenue per capita maximizes. O_{max}: Maximum expected revenue per capita.

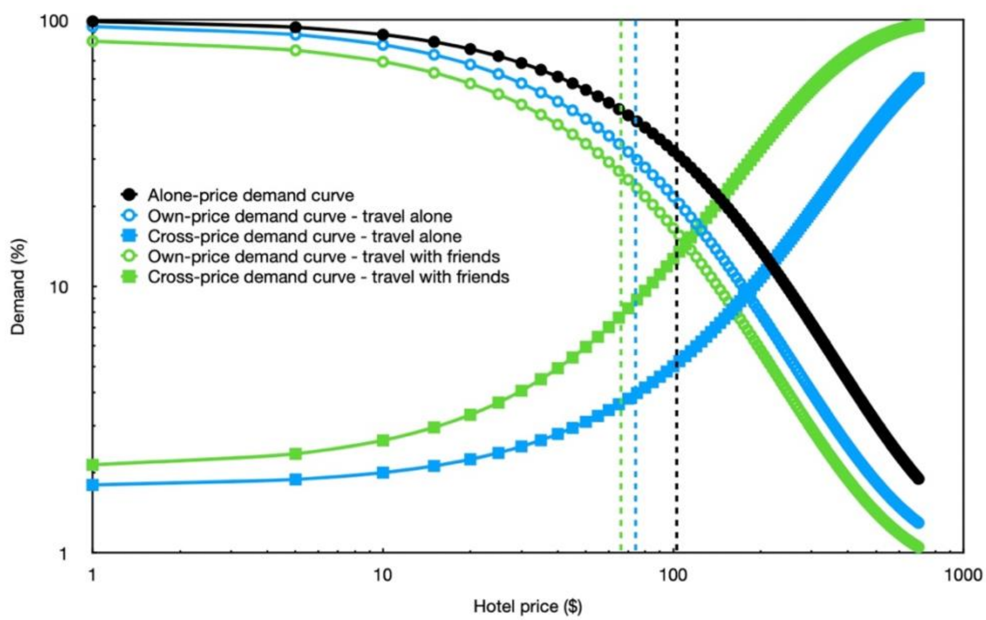


Figure 4.3 Demand curves for upscale hotels.

Similar to the above, there was a confirmed substitutive relationship between upscale hotels and sharing accommodation, as indicated by the negative interaction constants on all demand curves. The substitutability of sharing accommodation for upscale hotels was stronger when customers traveled with friends than when traveling alone. Additionally, we observed a more noticeable impact of sharing accommodation's entry into the market on the shape of the demand curve for upscale hotels, compared to economy and midscale hotels. In other words, with sharing accommodation entering the competition, customers' valuation of upscale hotels experienced the most significant decline. Furthermore, the disparity in own-price demand curves between different travel companion situations also appeared more marked for upscale hotels than for the other hotel types.

Table 4.4 Model results: upscale hotels.

	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)	Indifference price ($)
Alone-price demand curve (N = 225)	100^{***}	2.82^{***}			0.62	355	103	32	
Travel alone (N = 113)									180
Own-price demand curve	100^{***}	3.91^{***}	30.40^{**}	-0.27^{***}	0.58	256	74	22	
Cross-price demand curve	100^{**}		2.97^{***}	-1.75^{***}	0.25				
Travel with friends (N = 112)									111
Own-price demand curve	100^{***}	4.39^{***}	20.82^{***}	-0.46^{***}	0.53	228	66	18	
Cross-price demand curve	100^{***}		6.28^{***}	-1.68^{***}	0.29				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
EV: Inverse of the elasticity (decay rate) of demand curve; positively correlated with consumers' valuation of the good. P_{max}: Point of unit elasticity; the price where the expected revenue per capita maximizes. O_{max}: Maximum expected revenue per capita.

While sharing accommodation was confirmed as a substitute for all hotel types, the degree of substitution varied. The substitutability of sharing accommodation was the strongest for economy hotels, followed by midscale hotels and upscale hotels. Furthermore, the direction of the substitutive relationship influenced the conclusions. In Table 4.5, we extracted parameter βs (at 10^{-3}) from the own-price demand curves for hotels and the cross-price demand curves for sharing accommodation to examine whether the substitutability of hotels for sharing accommodation mirrored the substitutability of sharing accommodation for hotels. Since the own-price and cross-price demand curves were modeled in different functional forms, their parameters were not directly comparable. As a workaround, we analyzed the dual-directional rank orders of parameter β across hotels and found an asymmetric substitutive relationship. To reiterate, β represents the increase rate of the cross-price elasticities along the demand curve. A higher β from the own-price [cross-price] demand curve indicates that the demand for economy/midscale/upscale hotels [sharing accommodation] is more sensitive to sharing accommodation [economy/midscale/upscale hotel] price, thereby suggesting a stronger substitutability of economy/midscale/upscale hotels [sharing accommodation] for sharing accommodation [economy/midscale/upscale hotels].

The substitutability of sharing accommodation was greater for lower-end hotels. This implies that compared to midscale and upscale hotels, economy hotels would lose more customers to sharing accommodation with higher prices. When it came to hotels substituting for sharing accommodation, however, midscale hotels emerged as the strongest substitutes, defying the expectation of a symmetric relationship; and the following rank order slightly differed between traveling alone ($\beta_{economy} > \beta_{upscale}$) and traveling with friends ($\beta_{upscale} > \beta_{economy}$). This suggests that with higher sharing accommodation prices, customers tended to opt for higher-quality hotels as their accommodation substitutes, especially when traveling with friends. In fact, compared to traveling alone, the substitutability of sharing accommodation [hotels] for hotels [sharing accommodation] was consistently strengthened [weakened] when traveling with friends.

Table 4.5 Asymmetric substitution between sharing accommodation and hotels.

	Economy	**Midscale**	**Upscale**
Substitutability of sharing accommodation for hotels			
Travel alone	5.78	4.00	2.97
Travel with friends	9.74	6.34	6.28
Substitutability of hotels for sharing accommodation			
Travel alone	35.33	41.22	30.40
Travel with friends	18.58	21.15	20.82

4.4.3 Variations in the substitutive relationship across customers

To delve into the effects of customer characteristics on the substitutive relationship, we conducted additional analyses by segmenting participants based on gender, age (≤ 40 years vs. > 40 years), annual household income (< $80,000 vs. ≥ $80,000) and preference (frequent customers of a certain hotel type vs. other customers). Tables 4.6 to 4.9 provide insights into the substitutability of sharing accommodation for hotels (βs from the cross-price demand curves) and the substitutability of hotels for sharing accommodation (βs from the own-price demand curves) within each customer group, where "Ns" denotes an insignificant parameter. Similar to Table 4.5, a higher β means a stronger substitutability. See the Appendix D for detailed model results.

Table 4.6 The influence of gender.

		Economy	Midscale	Upscale
Substitutability of sharing accommodation for hotels				
Travel alone	Female	6.61	4.00	4.05
	Male	4.96		2.10
Travel with friends	Female	12.01	6.34	8.86
	Male	7.18		3.04
Substitutability of hotels for sharing accommodation				
Travel alone	Female	35.33	39.41	28.86
	Male		Ns	Ns
Travel with friends	Female	18.58	20.02	20.04
	Male		23.17	21.42

Females exhibited higher substitutability of sharing accommodation for hotels than males, except for midscale hotels. Among female customers, the substitutability of all hotel types for sharing accommodation was reduced when traveling with friends as opposed to traveling alone. A similar pattern was observed among male customers regarding the substitutability of economy hotels for sharing accommodation. However, males did not perceive midscale and upscale hotels as substitutes for sharing accommodation when traveling alone, and their hotel demand curves exhibited greater substitutability for sharing accommodation than those of females when traveling with friends. These findings suggest that females generally had a higher level of acceptance for sharing accommodation, whereas males might place a lower value on the home benefits of sharing accommodation. Furthermore, compared to females, males appeared to be more resistant to transitioning from hotels to sharing accommodation in response to increases in hotel prices. When traveling alone, their hotel preferences seemed to be primarily driven by absolute hotel prices; and when traveling with friends, they showed a greater willingness to switch from sharing accommodation to higher-end hotels as sharing accommodation price increased.

Table 4.7 The influence of age.

		Economy	Midscale	Upscale
Substitutability of sharing accommodation for hotels				
Travel alone	≤ 40 years	6.52	4.58	4.35
	> 40 years	5.04	3.60	2.05
Travel with friends	≤ 40 years	7.34	6.34	4.09
	> 40 years	14.40		8.23
Substitutability of hotels for sharing accommodation				
Travel alone	≤ 40 years	33.11	41.22	29.74
	> 40 years	40.54		Ns
Travel with friends	≤ 40 years	22.23	21.15	20.82
	> 40 years	14.72		

The substitutability of sharing accommodation for hotels was stronger when traveling with friends than when traveling alone, irrespective of whether customers were younger or senior. However, younger customers displayed slightly greater resistance to transitioning from upscale hotels to sharing accommodation as the price of upscale hotels increased when traveling with friends than when traveling alone, implying that younger customers found upscale hotels more satisfactory for fulfilling their accommodation needs when traveling in a group. Senior customers, compared to their younger counterparts, were more sensitive to the influence of travel companions on their judgment. These indicate that senior customers, likely due to their extensive travel experience, showed a heightened awareness of the benefits associated with selecting an entire home in sharing accommodation when traveling with friends on a leisure trip. Nonetheless, senior customers did not consider upscale hotels as substitutes for sharing accommodation when traveling alone, meaning that they did not alter their demand for upscale hotels based on sharing accommodation prices.

Table 4.8 The influence of income.

		Economy	**Midscale**	**Upscale**
Substitutability of sharing accommodation for hotels				
Travel alone	< \$80,000	4.65	4.00	3.32
	≥ \$80,000	7.80		2.63
Travel with friends	< \$80,000	8.35	6.34	3.69
	≥ \$80,000	12.24		9.38
Substitutability of hotels for sharing accommodation				
Travel alone	< \$80,000	32.77	39.27	29.20
	≥ \$80,000	38.32	49.12	31.26
Travel with friends	< \$80,000	19.68	20.54	22.12
	≥ \$80,000	17.43	21.35	19.17

High-income customers were more sensitive to the price increase in economy hotels than low-income customers and more willing to choose the sharing accommodation as an alternative, especially when traveling with friends. However, high-income customers were resistant to substitute upscale hotels for sharing accommodation despite a price increase when traveling alone. In contrast, income did not significantly affect how midscale hotels were substituted by sharing accommodation. When traveling alone, the substitutability of hotels for sharing accommodation was consistently higher among high-income customers than among low-income customers. On the contrary, in the case of traveling with friends, high-income customers presented lower substitutability of hotels (except for midscale hotels) for sharing accommodation than their low-income counterparts. The findings suggest that compared to low-income customers, high-income customers value the home benefits and social interaction offered by sharing accommodation to their travel groups to a higher degree.

Table 4.9 The influence of preference.

<table>
<tr><th></th><th></th><th>Economy</th><th>Midscale</th><th>Upscale</th></tr>
<tr><td colspan="5">Substitutability of sharing accommodation for hotels</td></tr>
<tr><td rowspan="2">Travel alone</td><td>Frequent customers</td><td rowspan="2">5.78</td><td>5.00</td><td rowspan="2">2.97</td></tr>
<tr><td>Other customers</td><td>3.16</td></tr>
<tr><td rowspan="2">Travel with friends</td><td>Frequent customers</td><td>7.86</td><td rowspan="2">6.34</td><td rowspan="2">6.28</td></tr>
<tr><td>Other customers</td><td>10.86</td></tr>
<tr><td colspan="5">Substitutability of hotels for sharing accommodation</td></tr>
<tr><td rowspan="2">Travel alone</td><td>Frequent customers</td><td>39.77</td><td>36.20</td><td>Ns</td></tr>
<tr><td>Other customers</td><td>32.22</td><td>Ns</td><td>31.58</td></tr>
<tr><td rowspan="2">Travel with friends</td><td>Frequent customers</td><td rowspan="2">18.58</td><td>23.38</td><td>21.74</td></tr>
<tr><td>Other customers</td><td>20.36</td><td>21.04</td></tr>
</table>

Among frequent customers of a certain hotel type, the substitutability of sharing accommodation for that hotel type was more insensitive to changes in travel companions, compared to other customers. Yet this pattern did not hold true for frequent customers of upscale hotels, who, in line with other customers, consistently indicated low substitutability of sharing accommodation for upscale hotels under all circumstances. In general, frequent customers of a particular hotel type revealed demand curves with lower substitutability of sharing accommodation for those hotels and higher substitutability of the hotels for sharing accommodation than other customers did, reflecting their habit persistence in hotel choices. However, when traveling alone, frequent customers of upscale hotels did not consider upscale hotels as substitutes for sharing accommodation, while frequent customers of midscale hotels displayed greater substitutability of sharing accommodation for midscale hotels compared to other customers. These observations underscore the diverse influences of consumption preferences on demand curves across different hotel types. The rich experience of staying in low-end hotels led to more conservative and stable demand for those hotels, while greater experience in high-end hotels reinforced the behavior that sharing accommodation and high-end hotels were consumed independently.

4.5 Conclusions

The thriving sharing accommodation market has enriched the lodging industry with unique products and services, igniting a fervent debate about the impact of sharing accommodation on hotel businesses. While prior research has produced varied conclusions, we have recognized a lack of demand-curve delineation regarding whether sharing accommodation and hotels act as substitutes or complements and to what extent. The principal objective of this study was to conduct a systematic examination of the substitutive relationship between sharing accommodation and hotels, with a particular focus on discerning variations in the degree of substitution across different hotel types. We delved deeper into understanding the influences of travel companions and customer groups on the substitutive relationship to provide valuable insights into the competition dynamics and offer more targeted guidance for business strategies.

4.5.1 Discussion on key findings

In line with the pricing structure, customers place the highest value on upscale hotels, followed by midscale and economy hotels. It has been confirmed that all hotel types have significant substitutive relationships with sharing accommodation, albeit to varying extents. The substitutability of sharing accommodation is the greatest for economy hotels and decreases sequentially for midscale and upscale hotels. The result corroborates many existing conclusions (Dogru et al., 2019; Zervas et al., 2017) but diverges from certain studies positing that midscale hotels experience the highest level of substitution by sharing accommodation (Guttentag & Smith, 2017). The variance can be attributed to the inconsistent measurements of substitution in previous research. Leveraging demand curves and the dynamics of own-price and cross-price elasticities, this study establishes a new framework for examining the substitutive relationship between sharing accommodation and hotels. The comparison between the alone-price and own-price demand curves for hotels offers additional evidence of the substitution of sharing accommodation for hotels. Specifically, the demand curves for hotels become overall more elastic with lower essential values and optimal pricing points upon the entry of sharing accommodation into the market. This shift is particularly pronounced for higher-end hotels. These findings align with prior research pointing that sharing accommodation exerts significant downward pressure on hotel prices (Dogru et al., 2022) and elevates the price elasticity of the hotel industry (Chen et al., 2022).

Moreover, this study represents the first effort to confirm that the substitutive relationship between sharing accommodation and hotels is asymmetric. Previous research predominantly emphasized the threats that sharing accommodation poses to hotel businesses while relatively overlooking the substitution of hotels for sharing accommodation. Our results reveal that, although the substitutability of sharing accommodation for hotels decreases as hotels ascend from low-end to high-end categories, midscale hotels present the greatest substitutability for sharing accommodation. The order of substitutability between economy and upscale hotels for sharing accommodation varies based on whether travel companions are present. Economy hotels exhibit greater substitutability than upscale hotels for sharing accommodation when traveling alone, whereas the opposite holds when traveling with friends. In other words, the demand for upscale hotels benefits more from the increase in sharing accommodation prices when traveling with friends than when traveling alone. This phenomenon reflects group travelers' requirements for higher-quality hotels in lieu of sharing accommodation.

Compared to solo travel, the attractiveness of sharing accommodation – a sense of community (Tussyadiah, 2015), enjoyment, home benefits (So et al., 2018), novelty and social interaction (Chi et al., 2021) – is significantly amplified when traveling with friends. Consequently, there is generally higher [lower] substitutability of sharing accommodation [all hotel types] for all hotel types [sharing accommodation] when traveling with friends than when traveling alone. It has been proved that entire homes have a more negative impact on hotel revenue than private or shared rooms (Dogru et al., 2020), and that travelers prefer sharing accommodation over hotels when accompanied by friends (Poon & Huang, 2017). These findings indirectly testify the observed variations in the substitutive relationship between sharing accommodation and hotels in different travel companion situations.

By further investigating how the substitutive relationship varies across customer groups, we uncover customers' divergent accommodation needs under different circumstances. When traveling alone, cost considerations take precedence over the living environment. Customers typically opt for economy hotels as an alternative to sharing accommodation, whereas higher-end hotels are not perceived as substitutes for sharing accommodation by certain customer groups. When traveling with friends, however, customers place a higher emphasis on the ambience and environment of their accommodation. Therefore, higher-end hotels substitute for sharing accommodation to a larger degree. This underscores customers' increased demands for the quality of hotel services and facilities to compensate sharing accommodation's home benefits. As a result, the competition between sharing accommodation and higher-end hotels intensifies when catering to group travelers as opposed to solo travelers.

4.5.2 Implications

This study addresses the research void in using demand curve analysis to assess the substitutive relationship between sharing accommodation and different hotel types. The behavioral economic demand models, serving as a better alternative to traditional econometric demand models, enable us to fit complete demand curves and parameterize the change rate of elasticity over the full price range. The degree of substitution is therefore comprehensively quantified based on the entire demand curve, in contrast to the prevailing practice in econometric demand modeling studies relying on single elasticity coefficients (Gunter & Önder, 2018). Furthermore, by employing the multivariate behavioral economic demand model, this study advances the fitting of hotel demand curves from a two-dimensional to three-dimensional construction. This study is the first application of the multivariate behavioral economic demand model to fit demand data in both tourism and behavioral economics research. Beyond clarifying the fluctuating substitutability of sharing accommodation for different hotel types, this study contributes to the limited literature on the substitutability of hotels for sharing accommodation and points out the asymmetric substitutive relationship between sharing accommodation and hotels. It also uncovers the influences of travel companions and customer characteristics, providing novel insights into the substitutive relationship and its variability across contexts.

From a practical perspective, these findings offer critical insights for both sharing accommodation and hotel businesses regarding market competition strategies. The substitutability of sharing accommodation for different hotel types highlights that the demand for sharing accommodation is most sensitive to the price of economy hotels. Therefore, a potential strategy for economy hotels to compete with sharing accommodation and retain their customers could involve reducing prices. On the flip side, the substitutability of each hotel type for sharing accommodation suggests that midscale hotels are the primary alternative for customers if sharing accommodation prices increase. Hence, sharing accommodation could consider lowering prices to attract more customers from midscale hotels than from other hotels.

Importantly, industry managers should recognize that the competition between sharing accommodation and hotels is dynamic and varies across customer segments and contexts. For example, upscale hotels should be vigilant about price competition from sharing accommodation, which may lure away their group customers traveling with friends. While females generally have a higher acceptance of sharing accommodation than males, they are also more price-sensitive in both hotels and sharing accommodation, a customer segment sensitive to relative pricing changes. In contrast, males tend to be less responsive to price fluctuations, implying relatively stable competition to attract male customers. However, a reduction in sharing accommodation prices when traveling with friends could motivate male customers to switch from hotels to sharing accommodation. Furthermore, independent senior customers are likely to exhibit loyalty to hotels, whereas senior customers in groups may become a reliable customer source for sharing accommodation. Hotels may find it harder to lose their frequent customers compared to other customers when increasing their own prices. Given these considerations, managers of different lodging establishments are encouraged to develop customized market competition strategies that account for their customer structure and the dual-directional substitutive relationship with other competitors.

4.5.3 Limitations and future research

This study focused on three hotel types to maintain a manageable research scope, but we believe that conducting investigations into other hotel types (e.g., luxury hotels) and their substitutive relationship with sharing accommodation would further enhance our understanding of the lodging industry and its competitive landscape. Furthermore, real travel situations encompass various forms of travel companions beyond traveling alone or with friends, so future research should explore how sharing accommodation and hotels substitute for each other when customers travel with family, a partner or other companions.

Purpose of travel also influences customers' accommodation demand. Due to the limited length of this study, we control the purpose of travel to leisure trips only. Nonetheless, figuring out how the substitutive relationship between sharing accommodation and hotels varies between leisure trips and business trips is also a research direction that is worth exploring. Another noteworthy consideration is the analysis of shared rooms and their substitutive relationship with hotels. Additionally, it would be valuable to investigate how the degrees of substitution between sharing accommodation and hotels vary between domestic and outbound tourists. Finally, this study used experiments to collect hypothetical purchase data given the lack of secondary data sources with sufficient price points and individual consumer information. Yet we encourage future researchers to apply eligible secondary data to model actual consumer demand and its possible trends over time.

Chapter 5 Conclusions

This chapter concludes the thesis by summarizing the research findings and their implications. Section 5.1 synthesizes the key results from each of the three studies. Sections 5.2 and 5.3, respectively, delve into the theoretical and practical implications of these findings. Section 5.4 discusses the limitations of the current research and offers suggestions for future studies.

5.1 Summary of Key Findings

This thesis introduces "behavioral" behavioral economics to tourism research and applies the corresponding behavioral economic demand models to model tourism demand at the disaggregate level. The effectiveness of this novel methodology within the tourism context, as well as its advantages over traditional econometric demand models, are demonstrated through three individual studies.

Chapter 2 identifies four critical issues in current practices of tourism demand modeling. These issues include the reliance on the theoretical foundation of perfect rationality across various contexts, the assumption of homogeneous market individuals, and the use of widely applied econometric demand models that estimate constant elasticity coefficients and generate incomplete demand curves. To address these issues, the study introduces "behavioral" behavioral economics – one of the two branches of behavioral economics – along with its demand framework, encompassing both the demand models and the methods of data collection. This approach is adapted into a new conceptual model for quantifying tourism demand at the disaggregate level, thereby guiding future empirical applications. The conceptual model expands the definitions of price and demand, integrating individual differences and environmental factors as key variables for disaggregate modeling. This model also forms the foundation for the two subsequent empirical studies of the thesis.

Chapter 3 presents one of the pioneering empirical studies in tourism research to model demand at the disaggregate level. It examines the demand curves for three hotel types (economy, midscale and upscale) using a behavioral economic demand model. The study observes shifts in these demand curves between different consumption situations (normal vs. pandemic) and across various customer groups (by gender, age, income, preference and risk tolerance). The findings indicate that economy, midscale and upscale hotels are perceived as distinct goods by customers, each with significantly different demand curves. Upscale hotels exhibit the highest essential value, followed by midscale and economy hotels. The pandemic's impact varied, making the demand curve for midscale hotels more inelastic and that for upscale hotels more elastic. It also altered the influence of individual differences on the demand curves, though the demand curve for economy hotels remained largely unchanged during the pandemic. This was largely attributed to customers' prioritized balancing of health and financial risks in pandemic conditions. Additionally, the study identified consistent effects of customer characteristics on demand curves across hotel types. These include a more elastic demand curve among females compared to males, less pandemic responsiveness among young adults than middle-aged and older adults, and a positive correlation between hotel's essential value and customers' income, risk tolerance and consumption frequency.

Chapter 4 continues the exploration of behavioral economic demand models in tourism research by conducting the first empirical study to investigate the substitutive relationship between sharing accommodation and different hotel types (economy, midscale and upscale), using demand curve analysis. Utilizing these models, the study constructs alone-price and own-price demand curves for hotels, as well as cross-price demand curves for sharing accommodation in relation to hotel pricing. This approach quantifies the substitutability of sharing accommodation for each hotel type and vice versa. The findings reveal that sharing accommodation most significantly substitutes economy hotels, with its substitutability decreasing for higher-end hotels. Conversely, midscale hotels emerged as the strongest substitutes for sharing accommodation, indicating an asymmetric substitutive relationship between these lodging options. Further analysis of the demand curves, segmented by travel companion (traveling alone vs. with friends) and customer characteristics (gender, age and preference), shows that the substitution dynamics are variable. Specifically, the substitutability of sharing accommodation for hotels was higher, and that of hotels for sharing accommodation was lower, when traveling with friends compared to traveling alone. Additionally, the study finds that females have a higher propensity for choosing sharing accommodation over males, and senior customers show a greater responsiveness to the home benefits of sharing accommodation when traveling with friends than younger customers.

5.2 Theoretical Implications

This thesis is the first to introduce “behavioral” behavioral economics and its explanatory paradigm for demand modeling in the field of tourism. In contrast to the microeconomic underpinnings of most existing tourism demand modeling studies, “behavioral” behavioral economics offers an innovative theoretical framework for understanding and examining demand curves. On one hand, “behavioral” behavioral economics significantly expands the definitions of price (encompassing any [risk of] loss, such as money, time and energy) and demand (defined as the acquisition of any valued entity, including physical products and psychological states). This expansion broadens the applicability of demand curves as a quantitative tool for specifying consumer behavior. On the other hand, the framework enriches and advances the interpretation of elasticity, focusing on the overall dynamics of elasticity along the demand curve rather than on point elasticity at individual price levels. The dynamics of elasticity, as described in “behavioral” behavioral economics, define the properties of a good and are characterized by its essential value, which reflects the extent to which a good is deemed worth pursuing despite increasing costs (Hursh & Roma, 2013). These novel concepts hold the promise of elevating tourism demand modeling to a more comprehensive and micro-oriented level. “Behavioral” behavioral economics and its demand models have been adapted into tourism research, culminating in the establishment of a new conceptual model in Chapter 2. This model aims to guide future empirical applications and propel further research into deeper aspects of demand modeling, which is highly generalizable to different tourism sectors beyond the lodging sector to analyze disaggregate demand curves.

Through the construction of complete demand curves over the full price range and the analysis of elasticity dynamics along these curves using behavioral economic demand models, researchers can gain an in-depth understanding of the interaction between price and demand, and consequently, the variation of business revenue with price changes (i.e., the total revenue curve). This level of analysis has not been achieved by most previous demand modeling studies, which often rely on econometric methods to fit incomplete market demand curves. The total revenue curve is a crucial component of demand analysis as it can reveal the optimal pricing point for maximizing total revenue. Estimating elasticity as a constant coefficient along the demand curve is not only unrealistic in many economic scenarios but also hinders the identification of this optimal pricing point. A constant inelastic or elastic elasticity would incorrectly suggest that maximum revenue occurs at infinitely high or zero prices, respectively, while a unit elasticity implies no revenue change regardless of price variations (Song et al., 2009). Furthermore, the complete demand curves derived from behavioral economic demand models serve as a practical tool for analyzing substitution and complementation. The parameterized dynamics of cross-price elasticity delineate the entire cross-price demand curve, where a steeper rate of increase [decrease] indicates a stronger substitutive [complementary] relationship, in line with microeconomic principles.

Moreover, the methodology derived from "behavioral" behavioral economics offers flexibility in collecting and processing disaggregate demand data. Through two empirical studies set within the lodging sector, this thesis demonstrates that modeling tourism demand at the disaggregate level can reveal numerous details previously overlooked by traditional demand modeling practices. The own-price and cross-price demand curves for a particular good exhibit significant variability across different consumers and contexts. This leads to inconsistent dynamics of elasticity and variations in other derived parameters, such as essential value, optimal pricing point, maximum revenue, breakpoint price and the degree of substitution. These findings provide compelling evidence that modeling market demand curves based on the assumption of homogeneous individual demand curves at a statistical average is neither sufficient nor accurate for capturing the impact of individual differences and environmental factors on demand curves. Therefore, for demand studies aiming to offer more nuanced economic or managerial insights for business entities, utilizing the behavioral economic demand framework for disaggregate-level modeling is a more effective and insightful approach compared to traditional econometric demand modeling, which is more suitable for estimating market-wide demand and its changes with shifts in population distribution.

5.3 Practical Implications

One of the most significant managerial implications for the tourism industry is that the complete demand curve, as modeled by the behavioral economic demand models, identifies the optimal pricing point for maximizing business revenue. The findings regarding the heterogeneity of hotel demand curves across different consumer groups underscore the necessity for each hotel business to estimate and evaluate its unique demand curve. This approach ensures that the determined optimal pricing point and projected maximum revenue are more precise and tailored to the hotel's specific situation. The estimation results presented in this thesis provide a practical tool for individual businesses to develop their demand curves. This can be achieved by applying weights that match the hotel's customer composition to the estimated demand curve parameters by customer characteristic, as detailed in Chapter 3 (for the Chinese market) or Chapter 4 (for the US market). Beyond the lodging sector, other tourism sectors are also encouraged to establish their own business-specific demand curves. By employing the methodology demonstrated in this thesis, they can better inform their pricing strategies and revenue management practices.

Disaggregate demand curves, when analyzed in terms of customer characteristics, can help businesses identify their ideal customers who place relatively high essential value on the offered products or services. Concurrently, these curves enable the formulation of differentiated sales strategies for various customer groups, aiding in market share expansion. For example, the findings in Chapter 3 suggest that in China, the ideal customers for midscale hotels are middle-aged people with an upper-middle income, whereas upscale hotels should target high-income, frequent customers. In addition to managing these ideal customer segments, midscale and upscale hotels may consider implementing customized marketing promotions, such as price discounts, coupons and redeemable membership points, to attract a broader customer base. However, for economy hotels, the ideal customer profile is less distinct, indicating limited effectiveness of differentiated strategies across customer segments. Given that economy hotels are generally perceived as a basic lodging option, they should focus on maintaining a stable and straightforward business strategy, offering limited yet satisfactory services at affordable prices.

The observed impacts of a pandemic on the demand curves of different hotel types provide valuable insights for hotel businesses in formulating coping strategies during a health crisis. Specifically, economy hotels should maintain their existing business strategies while focusing on enhancing epidemic prevention measures and hygiene standards to alleviate health risk concerns among customers. Midscale hotels, which tend to be more popular during a health crisis, could consider increasing room rates to boost revenue. These hotels are likely to attract more senior adults, as well as frequent customers of economy hotels and sharing accommodation. Conversely, upscale hotels may benefit from slightly reducing room rates to appeal to the middle-income market or maintaining current rates, especially for young adults, during a health crisis. Nonetheless, the loyal frequent customers of upscale hotels, who attribute a steadily high essential value to these establishments, remain a crucial asset, even amidst a crisis.

Through examining the substitutive relationship between various hotel types and sharing accommodation, this thesis offers effective market competition strategies for each lodging category. Sharing accommodation poses a greater threat to economy hotels than to midscale or upscale hotels. Consequently, economy hotels should be cautious in increasing room rates to avoid losing customers to sharing accommodation. Instead, offering price discounts could be an effective strategy for these hotels to compete against sharing accommodation and gain a larger market share. Among the three hotel types, midscale hotels emerge as the strongest substitutes for sharing accommodation. Therefore, sharing accommodation can focus on competing with midscale hotels by offering more attractive pricing. Upscale hotels, in contrast, do not directly compete with sharing accommodation, particularly among independent travelers. However, their group customers might be enticed by lower prices from sharing accommodation options. Besides, it is recommended that both hotels and sharing accommodation consider customer characteristics when developing competitive strategies. For instance, sharing accommodation is generally more accepted by females than males. Senior customers tend to prefer hotels when traveling alone and are more inclined towards sharing accommodation when traveling with friends, compared to younger customers. Habit persistence also impacts customers' demand curves, suggesting that frequent customers are a reliable customer base for most lodging businesses in competitive markets.

5.4 Limitations and Future Research

This thesis employs the hypothetical purchase task technique to collect consumers' reported demand values, which may somewhat diminish the models' predictive validity for actual demand in real market settings. This challenge is inherent in all questionnaire-based methods (Roma et al., 2017). Given the lack of suitable secondary data sources, however, the hypothetical purchase task remains the best alternative for data collection currently available. Nevertheless, this issue is not intractable in the long term, particularly with ongoing advancements in smart devices and user databases that facilitate the generation of big data at the individual level. Future research is encouraged to utilize secondary demand data, where available, to enhance the practical relevance of model results. Additionally, a systematic comparison of the modeling performance between traditional econometric demand models and behavioral economic demand models should be conducted by fitting tourism demand data from secondary sources, despite existing evidence suggesting the superior performance of behavioral economic demand models over traditional linear or logarithmic linear econometric models in the field of “behavioral” behavioral economics (Yan et al., 2012).

In this thesis, the impact of customer characteristics on demand curves is measured on a single-dimensional basis, with participants segmented by one characteristic variable at a time while controlling other variables. While this approach accurately specifies the impact of each characteristic, it offers limited guidance for businesses on specific customer segmentation strategies. However, the methodology itself does not preclude multi-dimensional analysis. For instance, participants can be segmented into groups based on multiple characteristics (e.g., young females vs. young males vs. senior females vs. senior males), provided there is a sufficient sample size. Researchers can then rank the essential values derived from these group demand curves to gain a clearer understanding of ideal customer profiles and more deeply investigate how the substitutive or complementary relationship between two related products varies across these specifically defined customer groups.

Due to its focus on the demand side, this thesis assumes a stable level of supply and does not discuss market equilibrium. Future research would benefit from integrating the behavioral economic demand framework with the supply-demand structure to gain a more thorough understanding of how supply and demand interact at the disaggregate level. Addressing the dynamic nature of the market, including the entry and exit of businesses, can also add realism to the demand models. Consequently, the model results can inform more effective policy and business strategies, enabling policymakers to design interventions that consider both demand and supply, and helping businesses make informed decisions about pricing and capacity management.

Despite these limitations, the significant advantage of the behavioral economic demand framework in disaggregate demand modeling is evident. This thesis has successfully demonstrated the applicability of this innovative methodology in analyzing hotel demand, and broader applications in other sectors of the tourism industry are highly encouraged to further enrich the field of demand modeling research.

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Appendix A Hypothetical Purchase Task Questionnaire (Chapter 3)

English Version

Part 1. Hotel demand

[Treatment group 1. Economy hotel × Normal situation]

Imagine that you are living your normal life before the COVID-19 pandemic. You plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city for a 1-week leisure trip. You have your eye on a typical standard room in an economy hotel as one of your possible accommodation choices. (Note: economy hotels are equivalent to 2-star hotels or below.)

[Treatment group 2. Economy hotel × Pandemic situation]

The COVID-19 pandemic has not yet subsided in China; outbreaks of varying scales have continued to occur across the country since 2021. In this situation, you plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city that is not currently experiencing an outbreak for a 1-week leisure trip. You have your eye on a typical standard room in an economy hotel as one of your possible accommodation choices. (Note: economy hotels are equivalent to 2-star hotels or below.)

[Manipulation checks]

How would you rate the potential health risk in this trip? (Likert: 1 = very low; 7 = very high)

How would you rate the cost of staying in economy hotels? (Likert: 1 = very low; 7 = very high)

[If scenario is 'treatment group 2'] Please briefly state your key considerations when choosing hotels in the above scenario.

____

In the above scenario, what is your expected standard room rate of economy hotels in domestic first-tier cities?

¥______________

The following questions ask how likely you are to choose to stay in your preferred economy hotel at various prices.

Assumptions:

- The given price in each of the following questions is assumed to be the only available price for a standard room in economy hotels.
- The price does not affect room quality or service quality.
- You have the same income and savings that you have now.

Given the above scenario and assumptions, how likely (0% ~ 100%) are you to choose to stay in your preferred economy hotel if its standard room costs:

¥0	
¥80	
¥100	
¥130	
¥180	
¥230	
¥300	
¥400	
¥520	
¥670	
¥870	
¥1,150	
¥1,500	

[Treatment group 3. Midscale hotel × Normal situation]

Imagine that you are living your normal life before the COVID-19 pandemic. You plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city for a 1-week leisure trip. You have your eye on a typical standard room in a midscale hotel as one of your possible accommodation choices. (Note: midscale hotels are equivalent to 3- to 4-star hotels.)

[Treatment group 4. Midscale hotel × Pandemic situation]

The COVID-19 pandemic has not yet subsided in China; outbreaks of varying scales have continued to occur across the country since 2021. In this situation, you plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city that is not currently experiencing an outbreak for a 1-week leisure trip. You have your eye on a typical standard room in a midscale hotel as one of your possible accommodation choices. (Note: midscale hotels are equivalent to 3- to 4-star hotels.)

[Manipulation checks]

How would you rate the potential health risk in this trip? (Likert: 1 = very low; 7 = very high)

How would you rate the cost of staying in midscale hotels? (Likert: 1 = very low; 7 = very high)

[If scenario is 'treatment group 4'] Please briefly state your key considerations when choosing hotels in the above scenario.

____

In the above scenario, what is your expected standard room rate of midscale hotels in domestic first-tier cities?

¥_______________

The following questions ask how likely you are to choose to stay in your preferred midscale hotel at various prices.

Assumptions:

- The given price in each of the following questions is assumed to be the only available price for a standard room in midscale hotels.
- The price does not affect room quality or service quality.
- You have the same income and savings that you have now.

Given the above scenario and assumptions, how likely (0% ~ 100%) are you to choose to stay in your preferred midscale hotel if its standard room costs:

¥0	
¥120	
¥150	
¥200	
¥260	
¥350	
¥450	
¥580	
¥770	
¥1,000	
¥1,300	
¥1,700	
¥2,250	

[Treatment group 5. Upscale hotel × Normal situation]

Imagine that you are living your normal life before the COVID-19 pandemic. You plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city for a 1-week leisure trip. You have your eye on a typical standard room in an upscale hotel as one of your possible accommodation choices. (Note: upscale hotels are equivalent to 5-star hotels.)

[Treatment group 6. Upscale hotel × Pandemic situation]

The COVID-19 pandemic has not yet subsided in China; outbreaks of varying scales have continued to occur across the country since 2021. In this situation, you plan to take a 1.5-hour flight or a 4-hour high-speed train to a domestic first-tier city that is not currently experiencing an outbreak for a 1-week leisure trip. You have your eye on a typical standard room in an upscale hotel as one of your possible accommodation choices. (Note: upscale hotels are equivalent to 5-star hotels.)

[Manipulation checks]

How would you rate the potential health risk in this trip? (Likert: 1 = very low; 7 = very high)

How would you rate the cost of staying in upscale hotels? (Likert: 1 = very low; 7 = very high)

[If scenario is 'treatment group 6'] Please briefly state your key considerations when choosing hotels in the above scenario.

____

In the above scenario, what is your expected standard room rate of upscale hotels in domestic first-tier cities?

¥_______________

The following questions ask how likely you are to choose to stay in your preferred upscale hotel at various prices.

Assumptions:

- The given price in each of the following questions is assumed to be the only available price for a standard room in upscale hotels.
- The price does not affect room quality or service quality.
- You have the same income and savings that you have now.

Given the above scenario and assumptions, how likely (0% ~ 100%) are you to choose to stay in your preferred upscale hotel if its standard room costs:

¥0	
¥160	
¥200	
¥270	
¥350	
¥460	
¥600	
¥780	
¥1,000	
¥1,300	
¥1,750	
¥2,300	
¥3,000	

Part 2. Personality and preferences

[Risk tolerance]

How do you rate your willingness to take risks in general areas of your life?

- ○ Extremely low (1)
- ○ ……
- ○ Extremely high (7)

What do your best friends think about you?

- ○ I take a lot of risks. (4)
- ○ I take risks sometimes, but always check in advance what may happen. (3)
- ○ I am cautious. (2)
- ○ I never take risks. (1)

[Travel preferences]

Please indicate your travel preferences in domestic leisure trips in the normal situation and in the pandemic situation, respectively.

	Domestic leisure trips per year	Usual travel companion	Usual travel organization	Usual accommodation choice
Normal situation	◦ None ◦ 1 ~ 2 trips ◦ 3 ~ 4 trips ◦ 5 ~ 6 trips ◦ 7 ~ 10 trips ◦ More than 10 trips	◦ Alone ◦ With family ◦ With friends	◦ Independent tour ◦ Guided tour	◦ Economy hotels (2-star or below) ◦ Midscale hotels (3- to 4-star) ◦ Upscale hotels (5-star) ◦ B&B
Pandemic situation	◦ Same as above	◦ Same as above	◦ Same as above	◦ Same as above

Part 3. Sociodemographic information

Would you please indicate your gender?

- Male
- Female

How old are you?

_______________years old

Would you please indicate your marital status?

- Single
- Married
- Others

Would you please indicate your highest level of education?

- Junior college or lower
- Bachelor’s degree
- Postgraduate degree

Would you please indicate your employment status?

- Wage-employed
- Self-employed
- Unemployed
- Student
- Stay-at-home parent/spouse
- Retired
- Others

[If 'wage-employed' is selected] Would you please indicate your employer?

- State-owned enterprise
- Public institution
- Civil service
- Private enterprise
- Foreign-owned enterprise

How many people live in your household (including you)?

____

Do you have children under 18 years old?

- Yes
- No

[If 'yes' is selected] How many children under 18 years old do you have?

____

What is the annual net income (after tax) of your household?

- Below ¥68,000
- ¥68,000 ~ ¥98,000
- ¥98,000 ~ ¥137,000
- ¥137,000 ~ ¥239,000
- Above ¥239,000

Where do you live?

*[Chinese cities in a drop-down list]*_______________Province_______________City

Chinese Version

第 1 部分. 酒店需求

[实验组 1. 经济型酒店 × 正常情境]

设想您处在新冠疫情发生之前，生活中一切如常。您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的经济型酒店的标准间，作为可能的住宿选择之一。（注：经济型酒店相当于二星级酒店及以下）

[实验组 2. 经济型酒店 × 疫情情境]

如今国内新冠疫情还没有消退，2021 年以来各地区仍然时有不同规模的本地爆发。在当前情况下，您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个目前没有疫情的国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的经济型酒店的标准间，作为可能的住宿选择之一。（注：经济型酒店相当于二星级酒店及以下）

[操控检验]

您认为这次旅行的潜在健康风险 (Likert: 1 = 非常低; 7 = 非常高)

您认为经济型酒店的住宿费用 (Likert: 1 = 非常低; 7 = 非常高)

[如果情境为'实验组 2'] 请简要列出您在上述情境下选择酒店的几个主要考虑因素。

____

在上述情境下，您对国内一线城市的经济型酒店标准间的预期价格是每晚多少元？

________________元

接下来的一系列问题需要您回答，在不同房价下，您选择入住这家酒店的可能性是多少。

假设:

- 以下每一个题目给出的房价都是当前市场上经济型酒店标准间的唯一价格；
- 房价的浮动不会影响酒店的房间质量和服务质量；
- 您的收入和储蓄维持现有水平不变。

在上述情境和假设下，

如果您心仪的经济型酒店标准间的价格是	**您选择入住的可能性是（0% ~ 100%）**
¥0	
¥80	
¥100	
¥130	
¥180	
¥230	
¥300	
¥400	
¥520	
¥670	
¥870	
¥1150	
¥1500	

[实验组 3. 中档酒店 × 正常情境]

设想您处在新冠疫情发生之前，生活中一切如常。您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的中档酒店的标准间，作为可能的住宿选择之一。（注：中档酒店相当于三至四星级酒店）

[实验组 4. 中档酒店 × 疫情情境]

如今国内新冠疫情还没有消退，2021 年以来各地区仍然时有不同规模的本地爆发。在当前情况下，您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个目前没有疫情的国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的中档酒店的标准间，作为可能的住宿选择之一。（注：中档酒店相当于三至四星级酒店）

[操控检验]

您认为这次旅行的潜在健康风险 (Likert: 1 = 非常低; 7 = 非常高)

您认为中档酒店的住宿费用 (Likert: 1 = 非常低; 7 = 非常高)

[如果情境为'实验组 4'] 请简要列出您在上述情境下选择酒店的几个主要考虑因素。

____

在上述情境下，您对国内一线城市的中档酒店标准间的预期价格是每晚多少元？

______________元

接下来的一系列问题需要您回答，在不同房价下，您选择入住这家酒店的可能性是多少。

假设:

- 以下每一个题目给出的房价都是当前市场上中档酒店标准间的唯一价格;
- 房价的浮动不会影响酒店的房间质量和服务质量;
- 您的收入和储蓄维持现有水平不变。

在上述情境和假设下,

如果您心仪的中档酒店标准间的价格是	**您选择入住的可能性是** **(0% ~ 100%)**
¥0	
¥120	
¥150	
¥200	
¥260	
¥350	
¥450	
¥580	
¥770	
¥1000	
¥1300	
¥1700	
¥2250	

[实验组 5. 高档酒店 × 正常情境]

设想您处在新冠疫情发生之前，生活中一切如常。您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的高档酒店的标准间，作为可能的住宿选择之一。（注：高档酒店相当于五星级酒店）

[实验组 6. 高档酒店 × 疫情情境]

如今国内新冠疫情还没有消退，2021 年以来各地区仍然时有不同规模的本地爆发。在当前情况下，您要从家出发，乘坐 1.5 小时的飞机或者 4 小时的高铁，到某个目前没有疫情的国内一线城市进行为期一周的休闲旅游。您看中了一家心仪的高档酒店的标准间，作为可能的住宿选择之一。（注：高档酒店相当于五星级酒店）

[操控检验]

您认为这次旅行的潜在健康风险 (Likert: 1 = 非常低; 7 = 非常高)

您认为高档酒店的住宿费用 (Likert: 1 = 非常低; 7 = 非常高)

[如果情境为'实验组 6'] 请简要列出您在上述情境下选择酒店的几个主要考虑因素。

____

在上述情境下，您对国内一线城市的高档酒店标准间的预期价格是每晚多少元？

______________元

接下来的一系列问题需要您回答，在不同房价下，您选择入住这家酒店的可能性是多少。

假设:

- 以下每一个题目给出的房价都是当前市场上高档酒店标准间的唯一价格;
- 房价的浮动不会影响酒店的房间质量和服务质量;
- 您的收入和储蓄维持现有水平不变。

在上述情境和假设下，

如果您心仪的高档酒店标准间的价格是	**您选择入住的可能性是** **（0% ~ 100%）**
¥0	
¥160	
¥200	
¥270	
¥350	
¥460	
¥600	
¥780	
¥1000	
¥1300	
¥1750	
¥2300	
¥3000	

第 2 部分. 性格与偏好

[风险承受度]

您在平常生活中承担风险的意愿

- ○ 非常低 (1)
- ○ ……
- ○ 非常高 (7)

您的好朋友们会如何评价您?

- ○ 我承担很多风险 (4)
- ○ 我有时会承担风险，但是总会提前考虑可能发生的结果 (3)
- ○ 我小心谨慎 (2)
- ○ 我从来都不承担风险 (1)

[旅游偏好]

请回答您在一般情况下和疫情情况下的国内休闲旅游偏好。

	一年中休闲旅游的次数	**通常的旅行伴侣**	**通常的旅行方式**	**通常的住宿选择**
一般情况下	◦ 0 次 ◦ 1 ~ 2 次 ◦ 3 ~ 4 次 ◦ 5 ~ 6 次 ◦ 7 ~ 10 次 ◦ 10 次以上	◦ 独自旅行 ◦ 和家人一起旅行 ◦ 和朋友一起旅行	◦ 自由行 ◦ 报旅行团旅行	◦ 经济型酒店(二星级及以下) ◦ 中档酒店(三至四星级) ◦ 高档酒店(五星级) ◦ 民宿
疫情情况下	◦ 同上	◦ 同上	◦ 同上	◦ 同上

第 3 部分. 社会人口信息

请选择您的性别

- ○ 男
- ○ 女

请输入您的年龄

______________岁

请选择您的婚姻状况

- ○ 未婚
- ○ 已婚
- ○ 其它

请选择您的最高学历

- ○ 专科或以下
- ○ 本科
- ○ 硕士或以上

请选择您的就业状况

- ○ 就业，受薪雇员
- ○ 就业，自雇人士
- ○ 失业
- ○ 在校学生
- ○ 料理家务
- ○ 离退休
- ○ 其它

[如果'就业，受薪雇员'已选定] 请选择您的工作单位

- ○ 国有企业
- ○ 事业单位
- ○ 公务员
- ○ 民营企业
- ○ 外资企业

您家庭的常住人口（包括您自己）有多少人？

______________人

您是否有 18 岁以下的未成年子女?

- ○ 是
- ○ 否

[如果'是'已选定] 您有几个未成年子女?

______________个

您家庭一年的税后收入是

- ○ 低于¥68000
- ○ ¥68000 ~ ¥98000
- ○ ¥98000 ~ ¥137000
- ○ ¥137000 ~ ¥239000
- ○ ¥239000 以上

请选择您的常住城市

*[中国城市下拉菜单]*______________省______________市

Appendix B Hypothetical Purchase Task Questionnaire (Chapter 4)

Part 1. Hotel Purchase Task

3 (*hotel type*: economy / midscale / upscale) × 2 (*travel companions*: travel alone / travel with friends)

[Scenario description – Alone price]

[Sample image for economy hotels]

[Sample image for midscale hotels]

[Sample image for upscale hotels]

Please imagine that you are going to travel **alone/with a group of friends** to a domestic urban city outside your usual residence for a one-week leisure trip. You need to book an accommodation for **yourself/everyone**.

There are no sharing accommodation options (e.g., Airbnb) in this city, but different types of traditional hotels (economy, midscale, and upscale) are available for your consideration. After searching, you have your eye on the typical standard **room/rooms** in an **economy/midscale/upscale** hotel.

[Manipulation check – Travel companion]

How do you feel about the following statement when you travel as described in the above scenario? In this trip, I make decisions on my travel activities alone.

- Strongly disagree (1)
- …
- Neither agree nor disagree (4)
- …
- Strongly agree (7)

[Manipulation check – Hotel type]

How would you rate the cost of staying in **economy/midscale/upscale** hotels relative to other hotel types?

- Very low (1)
- …
- Moderate (4)
- …
- Very high (7)

Given the above scenario, the following questions reflect how likely (0% ~ 100%) you are to choose to stay in your preferred **economy/midscale/upscale** hotel at various prices. Please read the assumptions below before you proceed.

Assumptions:

- The given price in each of the following questions is assumed to be the only available price for an **economy/midscale/upscale** hotel (standard room).
- You have the same income and savings that you have now.
- The price does not affect room quality or service quality.
- Apart from choosing your preferred **economy/midscale/upscale** hotel at a given price, you may also consider other hotel types, which are assumed to be at their average market prices.

How likely (0% ~ 100%) are you to choose to stay in your preferred **economy/midscale/upscale** hotel if a standard room costs … per night?

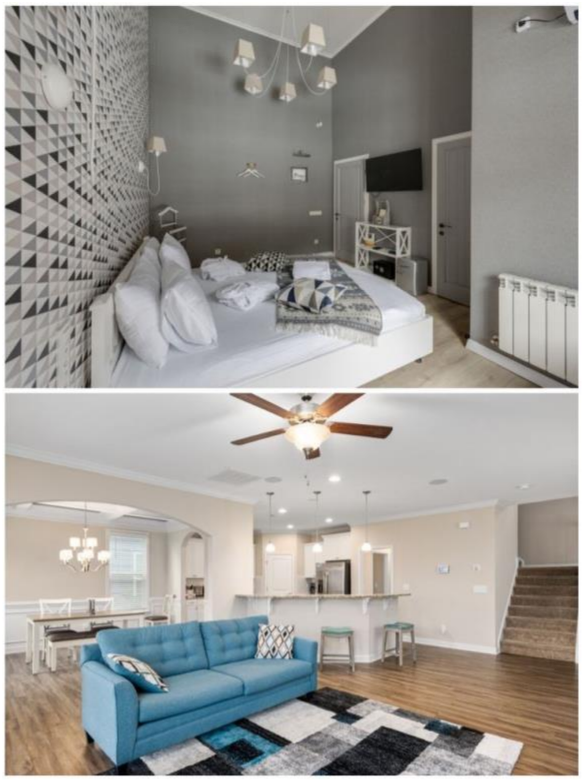
$0	…%
$20/$35/$50	…%
$35/$60/$80	…%
$60/$100/$140	…%
$100/$170/$240	…%
$175/$300/$400	…%
$300/$500/$700	…%

[Stop showing new price if hotel demand reaches 0%]

[Show this question when hotel demand > 0% at the 7th price point] You will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if the hotel's standard room rate is more than:

Please enter a number in US dollars:

[Scenario description – Own price & cross price]



[Sample image for sharing accommodation]

Please imagine that you are going to travel **alone/with a group of friends** to a domestic urban city outside your usual residence for a one-week leisure trip. You need to book an accommodation for **yourself/everyone**. After searching, you have your eye on the typical standard **room/rooms** in an **economy/midscale/upscale** hotel.

Now, in the travel scenario described above, the only change is that:

In addition to different types of traditional hotels, there are sharing accommodation options (e.g., Airbnb) available in this city. You may rent **a private room (i.e., your own room in a home plus some shared common space)/an entire home (i.e., a space with multiple bedrooms belonging only to your travel group)** that you like.

The following questions ask how likely (0% ~ 100%) you are to choose to stay in your preferred **economy/midscale/upscale** hotel and sharing accommodation, respectively, at various prices. Please read the assumptions below before you proceed.

Assumptions:

- The given pair of prices in each of the following questions is assumed to be the only available price for **an/a economy/midscale/upscale** hotel (standard room) and sharing accommodation (**private room/entire home**), respectively.
- You have the same income and savings that you have now.
- The price does not affect room quality or service quality.
- Apart from choosing between your preferred **economy/midscale/upscale** hotel and sharing accommodation at the given prices, you may also consider other hotel types, which are assumed to be at their average market prices.

If given the following pair of prices,

- **Economy/midscale/upscale** hotel (standard room): … per room per night
- Sharing accommodation (**private room/entire home**): … **per room/per bedroom (on average)** per night

How likely (0% ~ 100%) are you to choose to stay in the **economy/midscale/upscale** hotel and sharing accommodation, respectively?

Please note: the total likelihood should equal 100%.

Sharing accommodation price	**Economy /Midscale /Upscale** hotel price	**Economy /Midscale /Upscale** hotel	Sharing accommodation	Others	Total *[Auto calculated to equal 100%]*
$0	$0	…%	…%	…%	…%
$0	**$20/$35/$50**	…%	…%	…%	…%
$0	**$35/$60/$80**	…%	…%	…%	…%
$0	**$60/$100/$140**	…%	…%	…%	…%
$0	**$100/$170/$240**	…%	…%	…%	…%
$0	**$175/$300/$400**	…%	…%	…%	…%
$0	**$300/$500/$700**	…%	…%	…%	…%
[Stop increasing hotel price if sharing accommodation demand reaches 100%]					

[Show this question when hotel demand > 0% at the 7th hotel price] Given that the price of the sharing accommodation is $0, you will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if its standard room rate is more than:
Please enter a number in US dollars:

$60	$0	…%	…%	…%	…%
$60	**$20/$35/$50**	…%	…%	…%	…%
$60	**$35/$60/$80**	…%	…%	…%	…%
$60	**$60/$100/$140**	…%	…%	…%	…%
$60	**$100/$170/$240**	…%	…%	…%	…%
$60	**$175/$300/$400**	…%	…%	…%	…%
$60	**$300/$500/$700**	…%	…%	…%	…%

[Stop increasing hotel price if sharing accommodation demand reaches 100%]

[Show this question when hotel demand > 0% at the 7th hotel price] Given that the price of the sharing accommodation is $60, you will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if its standard room rate is more than:
Please enter a number in US dollars:

$90	$0	…%	…%	…%	…%
$90	**$20/$35/$50**	…%	…%	…%	…%
$90	**$35/$60/$80**	…%	…%	…%	…%
$90	**$60/$100/$140**	…%	…%	…%	…%
$90	**$100/$170/$240**	…%	…%	…%	…%
$90	**$175/$300/$400**	…%	…%	…%	…%
$90	**$300/$500/$700**	…%	…%	…%	…%

[Stop increasing hotel price if sharing accommodation demand reaches 100%]

[Show this question when hotel demand > 0% at the 7th hotel price] Given that the price of the sharing accommodation is $90, you will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if its standard room rate is more than:
Please enter a number in US dollars:

$130	$0	…%	…%	…%	…%
$130	**$20/$35/$50**	…%	…%	…%	…%
$130	**$35/$60/$80**	…%	…%	…%	…%
$130	**$60/$100/$140**	…%	…%	…%	…%
$130	**$100/$170/$240**	…%	…%	…%	…%
$130	**$175/$300/$400**	…%	…%	…%	…%
$130	**$300/$500/$700**	…%	…%	…%	…%

[Stop increasing hotel price if sharing accommodation demand reaches 100%] *[Show this question when hotel demand > 0% at the 7th hotel price]* Given that the price of the sharing accommodation is $130, you will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if its standard room rate is more than: Please enter a number in US dollars: __________					
$180	$0	…%	…%	…%	…%
$180	**$20/$35/$50**	…%	…%	…%	…%
$180	**$35/$60/$80**	…%	…%	…%	…%
$180	**$60/$100/$140**	…%	…%	…%	…%
$180	**$100/$170/$240**	…%	…%	…%	…%
$180	**$175/$300/$400**	…%	…%	…%	…%
$180	**$300/$500/$700**	…%	…%	…%	…%
[Stop increasing hotel price if sharing accommodation demand reaches 100%] *[Show this question when hotel demand > 0% at the 7th hotel price]* Given that the price of the sharing accommodation is $180, you will definitely not (0% chance) choose the **economy/midscale/upscale** hotel if its standard room rate is more than: Please enter a number in US dollars: __________					

Part 2. Personal Information

What type of accommodation do you most often choose when you take leisure trips to domestic urban cities?

- Economy hotels, motels, hostels
- Midscale hotels
- Upscale hotels
- Luxury hotels, boutique hotels
- Sharing accommodation (e.g., bed & breakfast, guest house)
- Serviced apartment (a fully furnished apartment with a kitchen for short-/long-term rent)

With which gender do you most identify?

- ○ Female
- ○ Male
- ○ Non-binary / Third gender
- ○ Prefer not to say

How old are you?

Please enter a number:

____

Would you please indicate your marital status?

- ○ Single, never married
- ○ Married / Domestic partnership
- ○ Separated / Divorced / Widowed

Would you please indicate your highest level of education?

- ○ Below high school
- ○ High school
- ○ Technical/vocational training
- ○ Bachelor’s degree
- ○ Postgraduate degree

Would you please indicate your employment status?

- ○ Employed full-time
- ○ Employed part-time
- ○ Self-employed
- ○ Student
- ○ Retired
- ○ Stay-at-home parent/spouse
- ○ Unemployed
- ○ Other (please specify):

How many people live in your household?

Adults (18 years old or above)	
Children (between 11 and 18 years old)	
Children (under 11 years old)	

What is the annual net income of your household (after taxes and other necessary deductions)?

- Less than $20,000
- $20,000 ~ $39,999
- $40,000 ~ $59,999
- $60,000 ~ $79,999
- $80,000 ~ $99,999
- $100,000 ~ $119,999
- $120,000 ~ $139,999
- $140,000 ~ $159,999
- $160,000 ~ $179,999
- $180,000 and over
- Prefer not to disclose

Where do you live?

City	
State	

Appendix C Double-Log Demand Model vs. Behavioral Economic Demand Model (Chapter 4)

This section demonstrates the comparison between the model performance of the exponential demand model from "behavioral" behavioral economics and of the double-log (also known as log-log or log-linear) demand model popularly applied in econometric demand modeling. The model results presented in Tables 4.2 to 4.4 in this study are used for comparison.

The double-log demand model to fit the alone-price demand curve for hotels is written as:

$$log_{10}(Q) = log_{10}(A) + \eta_P log_{10}(P), \qquad (a)$$

where Q is hotel demand, P is hotel price, A is the interception, and η_P is the alone-price elasticity of hotel demand. This model is compared with Equation 4.2 in Section 4.3.3.

The double-log demand model to fit the cross-price demand curve for sharing accommodation is written as:

$$log_{10}(Q) = log_{10}(A) + \eta_X log_{10}(P_S), \qquad (b)$$

where Q is sharing accommodation demand, P_S is hotel price, A is the interception, and η_X is the cross-price elasticity of sharing accommodation demand. This model is compared with Equation 4.3 in Section 4.3.3.

The double-log demand model to fit the own-price demand curve for hotels is written as:

$$log_{10}(Q) = log_{10}(A) + \eta_P log_{10}(P) + \eta_X log_{10}(P_S), \qquad (c)$$

where Q is hotel demand, P is hotel price, P_S is sharing accommodation price, A is the interception, η_P is the own-price elasticity of hotel demand, and η_X is the cross-price elasticity of hotel demand. This model is compared with Equation 4.4 in Section 4.3.3.

Tables I to III present the estimation results of the double-log demand models compared to their exponential counterparts. As shown below, the behavioral economic demand model yields considerably higher goodness-of-fit than the double-log demand model in almost all cases, confirming the importance of integrating the dynamics of elasticity in improving the modeling performance. In contrast, the double-log demand model estimates demand elasticity as a constant value without considering the elasticity change with price (from inelastic values to elastic values). As a result, the point of unit elasticity that indicates the optimal pricing point to maximize revenue does not exist. In addition, the estimated elasticity coefficients (η_P and η_X) across the three hotel types are quite similar, including less information about the different shapes of the demand curve for different hotel types.

Table I Model results: economy hotels.

	Exponential demand model					Double-log demand model			
	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	A (%)	η_P	η_X	R^2
Alone-price demand curve	100^{***}	5.25^{***}			0.60	100^{***}	-0.44^{***}		0.33
Travel alone									
Own-price demand curve	100^{***}	5.47^{***}	35.33^{***}	-0.44^{***}	0.56	91^{***}	-0.68^{***}	0.24^{***}	0.39
Cross-price demand curve	100^{*}		5.78^{***}	-1.78^{***}	0.31	1^{***}		0.56^{***}	0.27
Travel with friends									
Own-price demand curve	100^{***}	5.69^{***}	18.58^{***}	-0.79^{***}	0.49	100^{***}	-0.63^{***}	0.35^{***}	0.37
Cross-price demand curve	100^{***}		9.74^{***}	-1.62^{***}	0.32	100^{***}		0.58^{***}	0.29

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table II Model results: midscale hotels.

	Exponential demand model					Double-log demand model			
	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	A (%)	η_P	η_X	R^2
Alone-price demand curve	100^{***}	3.75^{***}			0.64	100^{***}	-0.44^{***}		0.35
Travel alone									
Own-price demand curve	100^{***}	4.71^{***}	41.22^{**}	-0.34^{***}	0.62	100^{***}	-0.68^{***}	0.20^{***}	0.43
Cross-price demand curve	100^{**}		4.00^{***}	-1.76^{***}	0.29	1^{***}		0.53^{***}	0.27
Travel with friends									
Own-price demand curve	100^{***}	4.84^{***}	21.15^{***}	-0.57^{***}	0.55	56^{***}	-0.66^{***}	0.27^{***}	0.42
Cross-price demand curve	100^{***}		6.34^{***}	-1.54^{***}	0.27	2^{***}		0.51^{***}	0.28

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table III Model results: upscale hotels.

	Exponential demand model					Double-log demand model			
	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	A (%)	η_P	η_X	R^2
Alone-price demand curve	100^{***}	2.82^{***}			0.62	100^{***}	-0.42^{***}		0.34
Travel alone									
Own-price demand curve	100^{***}	3.91^{***}	30.40^{**}	-0.27^{***}	0.58	100^{***}	-0.64^{***}	0.17^{***}	0.41
Cross-price demand curve	100^{**}		2.97^{***}	-1.75^{***}	0.25	1^{***}		0.50^{***}	0.25
Travel with friends									
Own-price demand curve	100^{***}	4.39^{***}	20.82^{***}	-0.46^{***}	0.53	65^{***}	-0.65^{***}	0.22^{***}	0.42
Cross-price demand curve	100^{***}		6.28^{***}	-1.68^{***}	0.29	1^{***}		0.53^{***}	0.30

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Appendix D Model Results of Customer Groups (Chapter 4)

Customer Groups by Gender

Economy hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)
Alone-price demand curve	6.37^{*}								
Female		100^{***}	4.96^{***}			0.62	202	59	18
Male		100^{***}	5.63^{***}			0.57	178	52	16
Travel alone									
Own-price demand curve	1.38	100^{***}	5.47^{***}	35.33^{***}	-0.44^{***}	0.56	183	53	16
Cross-price demand curve [a]	4.02^{*}								
Female		100^{*}		6.61^{***}	-1.81^{***}	0.35			
Male		100		4.96^{*}	-1.76^{***}	0.27			
Travel with friends									
Own-price demand curve	1.18	100^{***}	5.69^{***}	18.58^{***}	-0.79^{***}	0.49	176	51	11
Cross-price demand curve [a]	9.75^{**}								
Female		100^{***}		12.01^{***}	-1.66^{***}	0.40			
Male		$100^{\wedge}$		7.18^{**}	-1.56^{***}	0.25			

Midscale hotels.

	F	***Q_0* (%)**	***α* (10^{-3})**	***β* (10^{-3})**	***I***	***R^2***	***EV***	***P_{max}* ($)**	***O_{max}* ($)**
Alone-price demand curve	0.75	100***	3.75***			0.64	267	77	24
Travel alone									
Own-price demand curve	5.08*								
Female		100***	4.48***	39.41**	-0.39***	0.61	223	65	20
Male		100***	5.01***	45.46	-0.29***	0.62	200	58	18
Cross-price demand curve [a]	1.79	100**		4.00***	-1.76***	0.29			
Travel with friends									
Own-price demand curve	88.70***								
Female		100***	5.39***	20.02***	-0.64***	0.58	185	54	13
Male		100***	4.22***	23.17***	-0.49***	0.51	237	69	19
Cross-price demand curve [a]	0.00	100***		6.34***	-1.54***	0.27			

Upscale hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)
Alone-price demand curve	9.89**								
Female		100***	2.63***			0.62	381	110	35
Male		100***	3.07***			0.62	326	95	30
Travel alone									
Own-price demand curve	13.14***								
Female		100***	4.04***	28.86**	-0.33***	0.60	248	72	21
Male		100***	3.76***	32.89	-0.20***	0.54	266	77	24
Cross-price demand curve [a]	6.10*								
Female		100**		4.05***	-1.89***	0.32			
Male		100		2.10*	-1.63***	0.19			
Travel with friends									
Own-price demand curve	20.53***								
Female		100***	4.61***	20.04***	-0.50***	0.58	217	63	16
Male		100***	4.05***	21.42***	-0.43***	0.45	247	72	19
Cross-price demand curve [a]	34.30***								
Female		100***		8.86***	-1.74***	0.41			
Male		100$^{\wedge}$		3.04**	-1.53***	0.19			

Customer Groups by Age

Economy hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	*I*	R^2	*EV*	P_{max} ($)	O_{max} ($)
Alone-price demand curve	0.19	100^{***}	5.25^{***}			0.60	191	55	17
Travel alone									
Own-price demand curve	10.08^{**}								
≤ 40 years		100^{***}	5.56^{***}	33.11^{***}	-0.52^{***}	0.54	180	52	15
> 40 years		100^{***}	5.36^{***}	$40.54^{\wedge}$	-0.34^{***}	0.56	187	54	17
Cross-price demand curve [a]	10.79^{**}								
≤ 40 years		100^{*}		6.52^{***}	-1.74^{***}	0.32			
> 40 years		100		5.04^{*}	-1.85^{***}	0.32			
Travel with friends									
Own-price demand curve	8.80^{**}								
≤ 40 years		100^{***}	5.86^{***}	22.23^{***}	-0.73^{***}	0.50	171	50	12
> 40 years		100^{***}	5.34^{***}	14.72^{***}	-0.90^{***}	0.44	187	54	10
Cross-price demand curve [a]	23.75^{***}								
≤ 40 years		100^{*}		7.34^{***}	-1.59^{***}	0.27			
> 40 years		100^{***}		14.40^{***}	-1.65^{***}	0.44			

Midscale hotels.

	F	$\boldsymbol{Q_0}$ **(%)**	***α*** **(10^{-3})**	***β*** **(10^{-3})**	***I***	$\boldsymbol{R^2}$	***EV***	$\boldsymbol{P_{max}}$ **($)**	$\boldsymbol{O_{max}}$ **($)**
Alone-price demand curve	5.42*								
≤ 40 years		100***	3.55***			0.62	282	82	26
> 40 years		100***	3.95***			0.67	253	73	23
Travel alone									
Own-price demand curve	0.72	100***	4.71***	41.22**	-0.34***	0.62	212	62	19
Cross-price demand curve [a]	17.16***								
≤ 40 years		100*		4.58***	-1.66***	0.28			
> 40 years		100		3.60**	-1.89***	0.32			
Travel with friends									
Own-price demand curve	2.32	100***	4.84***	21.15***	-0.57***	0.55	207	60	15
Cross-price demand curve [a]	2.01	100***		6.34***	-1.54***	0.27			

Upscale hotels.

	F	$\boldsymbol{Q_0}$ **(%)**	***α*** **(10^{-3})**	***β*** **(10^{-3})**	***I***	$\boldsymbol{R^2}$	***EV***	$\boldsymbol{P_{max}}$ **($)**	$\boldsymbol{O_{max}}$ **($)**
Alone-price demand curve	0.07	100***	2.82***			0.62	355	103	32
Travel alone									
Own-price demand curve	41.24***								
≤ 40 years		100***	4.27***	29.74*	-0.31***	0.54	234	68	20
> 40 years		100***	3.57***	35.88	-0.20***	0.62	280	81	25
Cross-price demand curve [a]	33.16***								
≤ 40 years		100***		4.35***	-1.77***	0.31			
> 40 years		100		2.05*	-1.79***	0.22			
Travel with friends									
Own-price demand curve	0.04	100***	4.39***	20.82***	-0.46***	0.53	228	66	18
Cross-price demand curve [a]	6.95**								
≤ 40 years		100**		4.09***	-1.51***	0.19			
> 40 years		100***		8.23**	-1.81***	0.44			

Customer Groups by Income

Economy hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} (\$)	O_{max} (\$)
Alone-price demand curve	47.00***								
< \$80,000		100***	6.08***			0.61	164	48	15
≥ \$80,000		100***	4.33***			0.59	231	67	21
Travel alone									
Own-price demand curve	3.70^								
< \$80,000		100***	5.79***	32.77**	-0.36***	0.54	173	50	15
≥ \$80,000		100***	5.10***	38.32***	-0.55***	0.57	196	57	17
Cross-price demand curve [a]	21.10***								
< \$80,000		100		4.65*	-1.80***	0.26			
≥ \$80,000		100**		7.80***	-1.79***	0.41			
Travel with friends									
Own-price demand curve	19.03***								
< \$80,000		100***	6.39***	19.68***	-0.75***	0.49	156	45	11
≥ \$80,000		100***	4.91***	17.43***	-0.84***	0.46	204	59	12
Cross-price demand curve [a]	19.68***								
< \$80,000		100**		8.35***	-1.70***	0.31			
≥ \$80,000		100***		12.24***	-1.53***	0.36			

Midscale hotels.

	F	***Q_0* (%)**	***α* (10^{-3})**	***β* (10^{-3})**	***I***	***R^2***	***EV***	***P_{max}* ($)**	***O_{max}* ($)**
Alone-price demand curve	77.87***								
< $80,000		100***	4.50***			0.67	222	65	20
≥ $80,000		100***	3.01***			0.63	332	96	30
Travel alone									
Own-price demand curve	151.28***								
< $80,000		100***	5.74***	39.27*	-0.31***	0.62	174	51	16
≥ $80,000		100***	3.83***	49.12^	-0.37***	0.63	261	76	24
Cross-price demand curve [a]	0.00	100**		4.00***	-1.76***	0.29			
Travel with friends									
Own-price demand curve	10.92**								
< $80,000		100***	5.12***	20.54***	-0.56***	0.58	195	57	15
≥ $80,000		100***	4.46***	21.35***	-0.60***	0.50	224	65	17
Cross-price demand curve [a]	1.36	100***		6.34***	-1.54***	0.27			

Upscale hotels.

	F	**Q_0 (%)**	**α (10^{-3})**	**β (10^{-3})**	***I***	**R^2**	***EV***	**P_{max} ($)**	**O_{max} ($)**
Alone-price demand curve	90.05***								
< $80,000		100***	3.46***			0.66	289	84	26
≥ $80,000		100***	2.19***			0.59	457	133	42
Travel alone									
Own-price demand curve	58.72***								
< $80,000		100***	4.42***	29.20*	-0.24***	0.60	226	66	20
≥ $80,000		100***	3.31***	31.26*	-0.29***	0.54	302	88	26
Cross-price demand curve [a]	5.64*								
< $80,000		100*		3.32***	-1.72***	0.26			
≥ $80,000		100		2.63**	-1.80***	0.24			
Travel with friends									
Own-price demand curve	120.82***								
< $80,000		100***	5.67***	22.12***	-0.38***	0.55	176	51	14
≥ $80,000		100***	3.26***	19.17***	-0.57***	0.51	307	89	22
Cross-price demand curve [a]	37.44***								
< $80,000		100*		3.69***	-1.61***	0.21			
≥ $80,000		100***		9.38***	-1.70***	0.43			

Customer Groups by Preference

Economy hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)
Alone-price demand curve	7.51^{**}								
Frequent customers		100^{***}	5.73^{***}			0.63	175	51	16
Other customers		100^{***}	4.98^{***}			0.58	201	58	18
Travel alone									
Own-price demand curve	$3.66^{\wedge}$								
Frequent customers		100^{***}	5.77^{***}	39.77^{*}	-0.41^{***}	0.57	173	50	15
Other customers		100^{***}	5.21^{***}	32.22^{***}	-0.47^{***}	0.53	192	56	16
Cross-price demand curve [a]	0.66	100^{*}		5.78^{***}	-1.78^{***}	0.31			
Travel with friends									
Own-price demand curve	0.93	100^{***}	5.69^{***}	18.58^{***}	-0.79^{***}	0.49	176	51	11
Cross-price demand curve [a]	18.95^{***}								
Frequent customers		$100^{\wedge}$		7.86^{**}	-1.80^{***}	0.35			
Other customers		100^{***}		10.86^{***}	-1.55^{***}	0.32			

Midscale hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} (\$)	O_{max} (\$)
Alone-price demand curve	22.21^{***}								
Frequent customers		100^{***}	3.40^{***}			0.64	294	85	27
Other customers		100^{***}	4.23^{***}			0.65	237	69	22
Travel alone									
Own-price demand curve	28.99^{***}								
Frequent customers		100^{***}	4.37^{***}	36.20^{*}	-0.32^{***}	0.64	229	66	20
Other customers		100^{***}	5.19^{***}	54.70	-0.36^{***}	0.59	193	56	17
Cross-price demand curve [a]	23.50^{***}								
Frequent customers		100^{**}		5.00^{***}	-1.72^{***}	0.31			
Other customers		100		3.16^{**}	-1.83^{***}	0.28			
Travel with friends									
Own-price demand curve	87.89^{***}								
Frequent customers		100^{***}	4.38^{***}	23.38^{***}	-0.49^{***}	0.56	228	66	18
Other customers		100^{***}	5.59^{***}	20.36^{***}	-0.65^{***}	0.54	179	52	13
Cross-price demand curve [a]	1.49	100^{***}		6.34^{***}	-1.54^{***}	0.27			

Upscale hotels.

	F	Q_0 (%)	α (10^{-3})	β (10^{-3})	I	R^2	EV	P_{max} ($)	O_{max} ($)
Alone-price demand curve	5.41^{*}								
Frequent customers		100^{***}	2.55^{***}			0.61	392	114	36
Other customers		100^{***}	2.91^{***}			0.62	343	100	31
Travel alone									
Own-price demand curve	129.84^{***}								
Frequent customers		100^{***}	2.81^{***}	31.73	-0.19^{***}	0.58	356	103	32
Other customers		100^{***}	4.34^{***}	31.58^{**}	-0.28^{***}	0.58	231	67	20
Cross-price demand curve [a]	0.98	100^{**}		2.97^{***}	-1.75^{***}	0.25			
Travel with friends									
Own-price demand curve	113.16^{***}								
Frequent customers		100^{***}	3.43^{***}	21.74^{*}	-0.34^{***}	0.53	292	85	24
Other customers		100^{***}	4.90^{***}	21.04^{***}	-0.51^{***}	0.53	204	59	16
Cross-price demand curve [a]	1.27	100^{***}		6.28^{***}	-1.68^{***}	0.29			

Notes:

$^{\wedge}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

[a] Cross-price demand curve for sharing accommodation.

EV: Inverse of the elasticity (decay rate) of demand curve; positively correlated with consumers' valuation of the good. P_{max}: Point of unit elasticity; the price where the expected revenue per capita maximizes. O_{max}: Maximum expected revenue per capita.