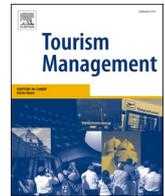


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A time-varying behavioral economic model for dynamic hotel demand analysis

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ABSTRACT

This study addresses the static limitations of current behavioral economic models by developing and empirically validating a novel time-varying behavioral economic model. Integrating a behavioral economic framework with nonlinear time-varying parameter estimation via a Bayesian approach, the model is empirically demonstrated through a hotel booking dataset. Results reveal significant heterogeneity in key behavioral characteristics (baseline demand and price sensitivity) across diverse customer segments (families vs. non-families, early vs. late bookers). Furthermore, these parameters evolve dynamically over time, exhibiting distinct seasonal patterns in price responsiveness, particularly in resort hotels. The proposed model provides a more granular understanding of consumer behavior, offering a robust tool for enhanced dynamic pricing, customer segmentation, and micro-targeted hotel management strategies in changing markets.

1. Introduction

Methodological innovation is paramount for advancing theoretical understanding of complex consumer behavior and informing robust tourism management strategies. For decades, tourism demand research has primarily relied on traditional econometric models. While these models have provided valuable insights into the responsiveness of demand to economic drivers such as price and income, they often assume rational consumers. Such assumptions risk oversimplifying the complexities in consumer behavior. They can mask the true variability in consumer price sensitivity across different price points and overlook significant heterogeneity among diverse consumer segments, thereby constraining the precision of demand forecasts and the efficacy of targeted strategies (Song & Lin, 2023).

Behavioral economics has emerged as a powerful alternative, providing an approach that relaxes the stringent assumptions of neo-classical theory to better capture the psychological realism of consumer choice. Behavioral economic demand models excel at characterizing how price elasticity varies dynamically across the price spectrum and in accounting for consumer heterogeneity, moving beyond the representative-agent paradigm (Lin, Chen, & Song, 2024). This allows

for a more nuanced understanding of how different consumer segments respond to pricing strategies. Despite these significant advancements in capturing price-dependent elasticity and heterogeneity, existing behavioral economic demand models applied in tourism and other fields are predominantly static. This imposes an important limitation, especially as tourism markets are increasingly subject to volatility and external disruptions. Such static models are not designed to capture how consumer price sensitivities and underlying valuations evolve over time in response to changing market conditions, seasonal trends, or external shocks (Peng et al., 2015).

Addressing this temporal gap is crucial, as tourism markets are fundamentally dynamic. The time-varying parameter (TVP) modeling technique offers a robust econometric solution for capturing such temporal dynamics, allowing model parameters to fluctuate over the study period (Song et al., 2011). The choice of a TVP framework is motivated by the inherently dynamic nature of consumer behavior in tourism. Willingness to pay and perceived value are rarely stable but fluctuate with seasonal cycles, holiday periods, economic conditions, external shocks, and past experiences. Fixed-parameter models, by assuming stability, risk oversimplifying these dynamics and producing biased estimates. By contrast, TVP models allow key behavioral parameters such

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as baseline demand and price sensitivity to evolve over time, aligning with both behavioral economic theory and the empirical reality of changing tourism markets.

While TVP models have enhanced traditional econometric analyses of tourism demand by revealing evolving elasticities, their underlying assumptions of neoclassical theory remain a limitation. Specifically, although traditional TVP models can show that parameters change over time, they may not explain how price sensitivity varies non-linearly across the full price spectrum at any given point in time. This study seeks to bridge this crucial gap by integrating a Bayesian nonlinear TVP model with a behavioral economic framework. This integration offers a significant advancement as it allows not only for the tracking of how behavioral parameters, such as baseline motivation or price sensitivity evolve temporally, but also ensures that these parameters are grounded in behavioral theories of consumer choice, capturing realistic, price-dependent elasticity dynamics. This approach provides a more granular and interpretable understanding of demand shifts.

Therefore, this study develops and empirically validates a time-varying behavioral economic model, an integrated framework that combines the strengths of behavioral economic modeling – specifically its capacity to model price-dependent elasticity and consumer heterogeneity – with the TVP technique’s ability to capture temporal variations in these behavioral parameters. Estimation of this complex nonlinear TVP model, often challenging for classical methods, is achieved using a Bayesian approach. By applying this novel model to a real-world hotel booking dataset, this study demonstrates how key behavioral characteristics (baseline demand and price sensitivity) evolve dynamically over time and differ across customer segments.

2. Literature review

2.1. Econometric modeling of tourism demand

Tourism demand modeling has progressively evolved from basic linear frameworks to more sophisticated econometric approaches that better reflect the complexity of consumer behavior (Song et al., 2009; Wu et al., 2022). Traditional models have been highly effective in capturing the overall responsiveness of tourism demand to key economic variables including income, prices, and exchange rates (Song et al., 2019) as well as other influencing factors such as customer reviews and environmental indices (Liu et al., 2025; Tang et al., 2019; Wu et al., 2024). Rooted in neoclassical microeconomic theory, they assume that consumers are rational decision-makers who optimize utility subject to budget constraints (Gilboa, 2010). Over decades, these models have supported policy development, destination marketing, and strategic planning, offering consistent and interpretable measures of economic responsiveness through elasticity estimates (Li et al., 2005; Song & Li, 2008).

Despite these valuable contributions, traditional econometric modeling continues to rely on simplifying assumptions that constrain its ability to represent consumer behavior with full realism. A central limitation is the reliance on constant-elasticity functional forms, such as the double-logarithmic (loglinear) specification, which mathematically enforce constant proportional responsiveness of demand to changes in prices or incomes (Dogru et al., 2017; Wen et al., 2018; Zhang et al., 2021). Under this specification, a 1 % change in price is assumed to generate a fixed percentage change in quantity demanded, regardless of the actual price level. While computationally convenient and suitable for stable environments, this functional form represents only a special case within the broader class of demand curves. In real-world settings, consumer sensitivity to price changes tends to vary systematically across different price ranges, often increasing at higher price levels where budget constraints become more binding or perceived value diminishes (Perloff, 2018). For instance, the elasticity of demand for luxury hotel stays may remain relatively low with moderate price increases but rise sharply as prices approach premium thresholds, reflecting nonlinear and

dynamic consumption responses. Such constant-elasticity models are limited in capturing these variations, thus limiting their ability to accurately map the full shape of demand curves across diverse pricing scenarios (Lin, Chen, & Song, 2024; Song & Lin, 2023).

Even when studies do not explicitly assume constant elasticity via the loglinear functional form, elasticity is typically estimated at the sample mean or evaluated around an average price level, resulting in a single constant elasticity measure (Song et al., 2009). Consequently, these models are equally limited in capturing, estimating, or parameterizing how elasticity systematically evolves across different points of the price spectrum. The resulting estimates reflect an average responsiveness rather than the full dynamic range of consumer sensitivity, further constraining the ability to accurately depict real-world demand behavior under varying pricing conditions.

A second important constraint of traditional econometric modeling in tourism demand is its predominant focus on aggregated market-level analysis (Song et al., 2019; Wu et al., 2022), which treats the entire consumer base as a homogeneous entity represented by a “representative agent” (Thomas, 1985). Although individual-level heterogeneity in preferences, price sensitivities, and decision processes is acknowledged in theory, it is largely omitted in empirical applications. In practical terms, market demand curves are constructed by simply aggregating across consumers without explicitly modeling differences between subgroups, such as tourists with varying demographic characteristics, motivational profiles, or travel party composition, thereby exhibiting distinct price sensitivities. This homogenizing approach masks substantial behavioral variation.

For example, young adults and senior travelers may exhibit markedly different price elasticities for the same destination or accommodation type (Lin, Chen, & Song, 2024). Similarly, adults traveling with companions may exhibit different price sensitivities compared to adults traveling alone when booking accommodations, reflecting differences in budget constraints, amenity needs, and flexibility in travel decisions (Lin, Chen, Li, & Song, 2024). By ignoring such differences, traditional econometric approaches limit their ability to generate nuanced insights necessary for micro-targeted marketing, differentiated pricing strategies, or demand management tailored to specific consumer segments (Song & Lin, 2023). This shortcoming is particularly problematic in contemporary tourism markets, where personalized experiences and dynamic pricing strategies increasingly define competitive advantage.

In summary, while traditional econometric modeling has provided a crucial empirical foundation for understanding macro-level tourism demand responses, its simplifying assumptions of constant elasticity and consumer homogeneity impose significant theoretical and practical limitations. These models succeed in offering broad market estimates but fall short of depicting the dynamic, heterogeneous realities of actual consumer behavior. Addressing these limitations requires moving beyond aggregate-level, constant-coefficient frameworks toward modeling approaches capable of systematically capturing elasticity dynamics across the price spectrum and behavioral heterogeneity across consumer groups. These challenges form the motivation for the development of more flexible, behaviorally grounded tourism demand models, a direction explored in the following section.

2.2. Behavioral economic demand modeling

Behavioral economic demand models represent a methodological advancement over traditional econometric approaches to tourism demand modeling by integrating insights from behavioral theory into the analysis of consumer choice (Hurst & Silberberg, 2008). While traditional models generally rely on the assumptions of fully rational agents and constant elasticity of demand that is often estimated around the average price level, behavioral economic demand models reject these restrictive premises. Instead, they account for behavioral heterogeneity and systematically model how consumer responses vary across price levels and individual characteristics (Song & Lin, 2023). This shift

enables more realistic representations of decision-making processes, particularly by capturing how tourists' price sensitivities differ depending on context and group composition.

A central methodological innovation of behavioral economic demand models lies in their explicit treatment of elasticity as a dynamic, price-dependent phenomenon. Rather than relying on constant-elasticity assumptions or estimating a single average elasticity, behavioral economic demand models focus on modeling how elasticity systematically varies across the full price spectrum (Hursh & Schwartz, 2023). This is achieved through the use of exponential decay-based demand functions such as the exponential model (Hursh & Silberberg, 2008), exponentiated model (Koffarnus et al., 2015), and zero-bounded model (Gilroy et al., 2021). These functional forms incorporate behavioral regularities observed in empirical data, where demand typically decays rapidly at higher price levels as consumers become more price sensitive.

This elasticity dynamic is captured through parameters that shape the curvature and steepness of the demand function, thereby reflecting how sensitivity evolves with price increments. In particular, behavioral economic demand models identify the acceleration rate at which demand "decays" with rising prices, a critical behavioral feature not easily retrieved from traditional econometric demand models. As Song and Lin (2023) emphasize, this capacitates researchers to distinguish between demand that remains less elastic and demand that is highly elastic at specific price points until an inflection occurs. This ability to parameterize elasticity dynamics enables more accurate mapping of full demand curves and supports more responsive and data-informed pricing strategies and public policies in the commercial market where small changes in cost can produce sharply differentiated consumer reactions across segments (Hursh & Roma, 2013; Schwartz & Hursh, 2023).

In addition to modeling elasticity dynamics, behavioral economic demand models introduce the concept of essential value, a parameter that captures the inherent strength of a consumer's valuation of a product or service independent of price. Essential value is derived from the curvature of the demand function and is inversely related to the acceleration rate at which demand declines with price. A high essential value indicates that demand is more resistant to price increases, suggesting a stronger reinforcement value of the good or service (Hursh, 2014). This innovation not only enhances interpretability but also facilitates cross-comparison of consumer valuation across different product types, segments, or scenarios (Oliveira-Castro et al., 2011; Roma et al., 2016; Schwartz et al., 2023). In the tourism context, this supports more effective market differentiation, demand forecasting, and value-based pricing strategies.

Another key contribution of behavioral economic demand models is their foundation in disaggregate analysis, allowing researchers to move beyond the representative-agent framework that characterizes traditional econometric demand modeling. While conventional approaches aggregate behavior at the market level and estimate average relationships, behavioral economic demand models are specifically constructed to preserve and analyze heterogeneity across individuals or consumer segments. This is especially important in tourism, where demand is shaped by factors such as demographics, preferences, and travel contexts, all of which may significantly influence how consumers respond to pricing (Chen et al., 2016, 2025; Li et al., 2020). However, a lot of demographic, psychographic, and situational characteristics are inherently masked in market-level aggregation.

Methodologically, behavioral economic demand models allow for the estimation of individual- or group-level demand curves based on behavioral parameters that capture the shape and sensitivity of consumption decisions, making it possible to model how different consumer segments respond across the price spectrum without imposing homogeneity in their behavioral profiles (Broadbent & Dakki, 2015; Reed et al., 2016; Schwartz & Hursh, 2022). Such modeling gives the means to the identification of consumer segments with varying thresholds of price tolerance and essential value (Lin, Chen, Li, & Song, 2024; Lin, Chen, &

Song, 2024). The disaggregated view is particularly valuable in applied contexts such as dynamic pricing, customer segmentation, and revenue management, where understanding fine-grained behavioral differences is essential for tailoring offerings and maximizing yield (Gelino et al., 2024; Reed et al., 2022).

Despite their methodological strengths, behavioral economic demand models exhibit one notable limitation: they are not inherently designed to capture how consumer price sensitivities evolve over time. While these models are highly effective in characterizing elasticity dynamics across the price spectrum, they remain static with respect to temporal variation. In real-world tourism markets, however, consumer behavior is rarely stable. Price responsiveness can fluctuate due to macroeconomic conditions, exogenous shocks (such as pandemics or geopolitical events), seasonal trends, and gradual shifts in consumer preferences (Peng et al., 2015; Smeral, 2017, 2018). Without the ability to accommodate such temporal changes, behavioral economic models may fail to reflect the dynamic nature of demand, thereby limiting their utility in strategic decision-making.

2.3. The TVP modeling technique

The TVP modeling technique represents a critical methodological advancement in tourism demand analysis, offering solutions to the limitations of static econometric models. These techniques have gained substantial popularity due to their capability to dynamically capture parameter changes, reflecting evolving consumer behavior and market conditions over time (Gunter & Önder, 2015; Jorge-González et al., 2019; Liang et al., 2024). Unlike traditional econometric models that assume fixed parameter values across the modeling period, TVP models allow elasticity and other demand parameters to fluctuate across the timeframe, thereby significantly enhancing the precision and relevance of demand modeling (Sun et al., 2021; Wu et al., 2022). This dynamic framework enables researchers to better account for the instability and non-stationarity that frequently characterize tourism demand systems.

Empirical applications of TVP modeling have demonstrated its superiority in depicting temporal heterogeneity in tourism demand. Specifically, Li et al. (2006) combined the TVP approach with linear almost ideal demand systems (TVP-LAIDS) to estimate and forecast tourism expenditure, showing that the time-varying framework more accurately fitted income and price sensitivities over time. Song et al. (2011) developed the TVP-STSM (structural time series model) and demonstrated that the TVP-enhanced framework offers more accurate forecasting performance compared to traditional time series models. Proposing a TVP panel vector autoregressive (TVP-PVAR) model, Wu et al. (2020) demonstrated that scenario forecasting can effectively capture the dynamic interactions between tourism growth and economic growth, highlighting the model's strength in dealing with global uncertainties and structural changes in tourism demand. In addition, the TVP technique has been proven effective in modeling tourism recovery from crises like COVID-19, capturing the crisis-induced demand volatility (Liu et al., 2024). These studies validate the practical effectiveness of the TVP modeling technique in generating robust and timely insights that static parameter approaches cannot provide.

In addition to their forecasting strength, TVP models offer important interpretive advantages. By modeling elasticity as a function of time rather than treating it as fixed, researchers can examine how consumer or investor responsiveness changes across different stages of market maturity, policy environments, or external disruptions (Gao et al., 2025; Hadi et al., 2023). For instance, TVP models estimate and visualize how income and price elasticities of demand fluctuate over time to various degrees across tourism destinations (Li et al., 2006; Wu et al., 2012). Furthermore, researchers have proven the effectiveness of TVP modeling in capturing the time-varying impacts of economic policy uncertainty and geopolitical risk on tourism demand, showing that the influence of these shocks fluctuates significantly over time and differs by event type and source (Gong et al., 2024; Guney et al., 2024; Ma et al., 2019; Zhang

et al., 2022). In contrast, the evolving influence of tourism on the macroeconomic environment can be explicitly quantified using the TVP approach (Lee et al., 2020). This temporal resolution makes TVP modeling a particularly valuable tool for both researchers and practitioners seeking to understand the dynamics of the tourism market and formulate prudent strategies.

While TVP models have enhanced traditional econometric analyses of tourism demand by revealing how elasticities change over time, their foundations remain tied to neoclassical assumptions. The above-mentioned TVP frameworks track the temporal evolution of elasticities in response to macro-level determinants such as prices, income and exchange rates. Despite their contribution, they do not explain how price sensitivity varies across the full price spectrum at a given point in time. Elasticity is treated as a constant proportionate response at each time step, meaning that the structure of the demand curve remains fixed even though the location of the curve shifts temporally.

The present study advances this literature by integrating the behavioral economic demand model within a TVP framework. This integration introduces a nonlinear representation of the demand curve that characterizes baseline demand and price sensitivity as behavioral parameters rather than purely statistical coefficients. More importantly, these parameters are allowed to vary through time. As a result, the model does not simply identify that elasticity changes but also reveals how the entire shape of the demand curve evolves both over time and across the full price range, which is not observable under loglinear or neoclassical TVP specifications. This capability makes it possible to quantify seasonal and segment-specific shifts in demand motivation and price tolerance, providing a level of behavioral resolution that conventional TVP models cannot deliver. The comparison summarized in Table 1 highlights these differences in terms of theoretical foundation, core parameters, elasticity structure, and ability to capture behavioral change.

The adoption of a TVP framework is both theoretically and empirically justified and it underpins the conceptual contribution of the proposed model. From a behavioral economics perspective, consumer demand evolves continuously, reflecting shifts in willingness to pay and perceived value driven by past experiences, seasonal travel patterns, holiday schedules, household budget changes, and market expectations (Lin et al., 2023). These behavioral drivers rarely remain constant over time, particularly in tourism markets that experience recurrent shocks and structural transitions. Empirical research likewise demonstrates that demand elasticities are unstable, varying across business cycles, crises, and recovery phases (Liu et al., 2024; Peng et al., 2015; Smeral, 2017, 2018). Fixed-parameter models, by assuming stability, tend to conflate genuine structural change with constant responses and therefore limit explanatory power. By allowing baseline demand and price sensitivity to evolve over time, the integrated behavioral economic TVP model captures this temporal heterogeneity rather than averaging it out. This makes it possible to interpret changes in pricing behavior through adjustments in consumers' underlying valuation rather than through aggregate coefficients. For management, this provides improved

visibility on how willingness to pay shifts across market segments and seasons, thereby offering a more reliable basis for dynamic pricing, inventory allocation, and market segmentation strategies.

3. Methods

3.1. Data

This study investigates the temporal heterogeneity of customer demand patterns in the hospitality market using real operational data. Due to the scarcity of longitudinal hotel booking datasets available for research, the analysis draws on the open-access "Hotel Booking Demand Dataset" published by Antonio et al. (2019), which is widely used by data science researchers and educators. The dataset comprises real transactional records from one city hotel in Lisbon and one resort hotel in the Algarve, including a total of 119,390 bookings made between July 2015 and August 2017. Each booking entry contains information including the average daily rate (ADR), number of booked nights, assigned room type, customer demographics, reservation channels, customer type, lead time, meal plan, whether the guest is a repeat customer, and cancellations/no-shows.

Room types A and D are selected because they represent the highest booking volumes in each hotel, though the dataset does not provide specifications for these categories due to anonymization. To maintain comparability in ADR and maximize sample size, only bookings with the "BB" (bed and breakfast) meal plan are included in the analysis. The dependent variable is the number of booked room nights, with ADR serving as the primary explanatory variable.

The dataset used in this study is one of the very few publicly accessible sources of detailed, longitudinal hotel booking records suitable for behavioral demand modeling. Its inclusion of two types of hotels provides a meaningful contrast between urban and leisure-oriented contexts. Although information such as star rating, size, or brand affiliation is anonymized, both hotels are large full-service properties with substantial booking volumes, ensuring robust sample sizes for behavioral and temporal estimation.

At the same time, some constraints of the dataset must be acknowledged. Room types are labeled generically without further specification of their features. However, the descriptive statistics in Table 2 suggest that D-rooms represent a higher-category room relative to A-rooms. In the city hotel, D-rooms show a higher mean ADR (€117.00 vs. €97.09) and lower skewness (0.33 vs. 0.75), indicating a more consistently premium pricing structure with fewer low-rate bookings. In the resort hotel, although mean ADRs are similar, D-rooms reach a higher maximum price (€315.38 vs. €289.00) and exhibit greater skewness (1.74 vs. 1.44), implying that they extend further into the premium range. These combined patterns provide reasonable grounds for treating D-rooms as a superior category, allowing the analysis to capture variation in price responsiveness across higher- and lower-priced tiers. While the operational scope is limited, the dataset offers a valuable empirical basis for demonstrating the methodological contribution of integrating

Table 1
Comparison of tourism demand modeling approaches.

Model	Theoretical foundation	Core parameters	Estimated elasticity structure	Capacity to capture behavioral change
Econometric model (e.g., linear, loglinear)	Neoclassical demand theory	Price and income elasticities	Constant across price range and time	Coefficients imply stable preferences and proportional responses
TVP-econometric model (e.g., TVP-LAIDS, TVP-STSM)	Neoclassical demand theory with temporal adaptation	Time-varying price and income elasticities	Varies over time but constant at average price level	Coefficients track temporal evolution but reflect proportional responses
Static behavioral economic model	Behavioral economics	Price elasticity dynamics (essential value) and baseline demand	Varies across price levels but fixed over time	Coefficients capture nonlinear curvature but no temporal dynamics
Proposed TVP-behavioral economic model	Behavioral economics with TVP framework	Time-varying price elasticity dynamics (essential value) and baseline demand	Varies across both price levels and time	Coefficients capture both nonlinear and temporal structural change in consumer valuation

Table 2
Descriptive statistics of bookings.

	Obs	ADR				Skewness	Nights				
		Mean	S.D.	Min	Max		Mean	S.D.	Min	Max	Skewness
City hotel A-room	21,022	97.09	27.67	1.00	254.00	0.75	2.98	1.67	1.00	34.00	1.88
City hotel D-room	9430	117.00	36.73	1.00	375.50	0.33	3.23	1.70	1.00	17.00	1.54
Resort hotel A-room	8071	74.91	46.85	4.00	289.00	1.44	3.85	3.00	1.00	56.00	2.08
Resort hotel D-room	6492	73.69	46.64	4.00	315.38	1.74	3.68	3.34	1.00	45.00	2.57

TVP techniques into behavioral economic demand modeling.

Due to the operational nature of the dataset, raw booking records often contain high variance, repeated ADR values paired with a wide range of room nights, and occasional extreme values that reflect atypical booking behavior (e.g., group reservations, deep-discount promotions). Such irregularities can distort the estimated shape of the demand curve and bias behavioral parameter estimates. Data preprocessing is therefore essential to ensure model stability, preserve interpretable behavioral relationships, and align the estimation process with theoretical expectations such as the inverse price–demand relationship.

To prepare the data for behavioral demand modeling, two preprocessing steps are undertaken to address high granularity and variance in the raw booking data. First, bookings are grouped by ADR value, using a €1 interval. Within each price interval, the average number of room nights is computed, effectively smoothing short-term volatility and allowing a more stable estimate of demand responses. This aggregation step integrates heterogeneity across booking channels, customer types, lead times, and seasons within each price band, meaning that subsequent filtering is applied to an already representative data structure rather than to individual transactions. Second, a quantile-based outlier filtering method is applied at each monthly time point to eliminate extreme observations that may distort parameter estimation. Specifically, bookings are excluded if both the ADR and the number of room nights fall below the 33rd percentile or above the 66th percentile of their respective monthly distributions. Mathematically, a data point $(ADR_i, Nights_i)$ was removed if:

$$\left(ADR_i < Q_{0.33}^{ADR} \wedge Nights_i < Q_{0.33}^{Nights} \right) \vee \left(ADR_i > Q_{0.66}^{ADR} \wedge Nights_i > Q_{0.66}^{Nights} \right)$$

where $Q_{0.33}$ and $Q_{0.66}$ represent the lower and upper tertiles, respectively. This outlier treatment is grounded in economic theory and past behavioral studies (Song & Lin, 2023; Stein et al., 2015), which assumes a negative relationship between price and demand, and helps retain observations consistent with expected behavioral patterns while excluding noise-prone or price-insensitive cases. Since this trimming is applied after interval aggregation, the procedure does not target individual booking records but only removes extreme price-demand points that depart from this principle. This reduces estimation bias and improves stability while minimizing the risk of systematically excluding meaningful heterogeneity. It is also worth noting that the ADRs in the dataset are posted prices observed by customers at the time of booking and set prior to the realized demand rather than being revised in response to individual transactions, which limits the potential for simultaneous determination of price and demand.

3.2. Behavioral economic demand model

The modeling framework employed in this study builds upon the exponential behavioral economic demand model originally developed by Hursh and Silberberg (2008). This model has been widely applied in behavioral economics to quantify how consumption responds to changes in price, providing elasticity measures that are grounded in behavioral principles rather than purely statistical associations. The original static model is specified as:

$$\log Q = \log Q_0 + k(e^{-\alpha Q_0 P} - 1)$$

where Q is the quantity demanded at price P , Q_0 captures the theoretical maximum demand at zero price which serves as the starting point of the demand curve, α governs the rate at which demand declines with price, reflecting the behavioral elasticity, k is the span parameter of $\log Q$ and set as $\log(Q_{max}) - \log(Q_{min}) + 0.1$ (Hursh & Silberberg, 2008).

In this structure, the shape of the demand curve is governed by Q_0 and α , representing consumers' baseline valuation and price sensitivity, respectively. A higher Q_0 reflects stronger intrinsic demand in the absence of price constraints, while a larger α indicates greater elasticity, with demand declining sharply in response to price increases. This parameterization allows simultaneous identification of both consumer motivation and price tolerance. For example, high Q_0 and low α characterize price-resilient segments typical of essential or high-commitment purchases, whereas low Q_0 and high α reflect marginal, luxury-driven demand that is highly sensitive to price changes.

For the hotel context, this approach offers several advantages. First, the exponential formulation captures the non-linear and diminishing relationship between price and demand, which reflects consumer behavior in hospitality markets where small price changes can lead to sharp adjustments in booking volumes up to a threshold, after which demand tapers more gradually. Second, the model produces elasticity estimates that have direct behavioral interpretation, allowing meaningful comparison of price sensitivity across customer groups. Third, the structure of the model enables researchers to analyze threshold effects and utility trade-offs, which are particularly relevant in contexts where heterogeneous consumer segments exhibit varying willingness to pay.

In this study, the exponential behavioral model is further extended by embedding it within a TVP framework. This extension allows the demand parameters to evolve over time, thereby accommodating shifts in consumer behavior that arise from seasonality, market trends, or external shocks. By integrating a theoretically grounded behavioral demand model with the flexibility of TVP estimation, the present approach provides a robust tool for capturing both the behavioral underpinnings of price responsiveness and the temporal fluctuations that characterize hotel demand.

3.3. TVP estimation with bayesian approach

To capture the temporal dynamics of the key behavioral parameters Q_0 and α , we specify a TVP model with a Bayesian approach. This specification allows Q_0 and α to evolve over discrete time periods (months, in this study) according to a random walk process. Specifically, for each time period t :

$$Q_{0,t} = Q_{0,t-1} + \omega_{Q_0,t}, \omega_{Q_0,t} \sim N(0, \sigma_{Q_0}^2)$$

$$\alpha_t = \alpha_{t-1} + \omega_{\alpha,t}, \omega_{\alpha,t} \sim N(0, \sigma_{\alpha}^2)$$

where $Q_{0,t}$ and α_t are the parameter values at time t . The terms $\omega_{Q_0,t}$ and $\omega_{\alpha,t}$ represent Gaussian noise (innovations) with a mean of zero and standard deviations σ_{Q_0} and σ_{α} , respectively. These standard deviations control the degree of temporal variation allowed for each parameter; larger values permit more rapid changes over time.

The log-transformed average room nights for observation i at time t are modeled as normally distributed around the prediction from the

nonlinear behavioral demand model:

$$\log Q_{i,t} \sim N(\mu_{i,t}, \sigma_\epsilon^2)$$

$$\mu_{i,t} = \log Q_{0,t} + k(e^{-\alpha Q_{0,t} P_{i,t}} - 1)$$

where $P_{i,t}$ is the ADR for observation i at time t , and σ_ϵ is the standard deviation of the observation error.

Given the complex nonlinear specification of the TVP model, estimation is performed using Bayesian inference via Markov Chain Monte Carlo (MCMC) simulation, implemented in Stan (Carpenter et al., 2017) through R (R Core Team, 2025). The Bayesian approach allows for the exploration of complex posterior distributions of the parameters that would be intractable with traditional frequentist methods. We specified priors for the initial states ($Q_{0,1}$, α_1) and the standard deviations of the random walks (σ_{Q_0} , σ_α) and the observation error (σ_ϵ) based on the results of static models. The priors for the initial parameters Q_0 and α were informed by the static behavioral economic model results, which provide a natural and empirically grounded reference for the means of the priors. Specifically, Q_0 was assigned $N(5, 1)$ and α was assigned $N(10^{-4}, 10^{-3})$, reflecting the central tendency and dispersion observed in the static estimates. The priors for the standard deviations σ_{Q_0} , σ_α , and σ_ϵ were specified as weakly informative half-normal priors, $N(0, 1)$ for σ_{Q_0} and σ_ϵ , and $N(0, 0.1)$ for σ_α to ensure non-negative and flexible variance estimates without unduly constraining parameter dynamics. The models were run with 4 parallel MCMC chains, each for 6000 iterations, with the first 3000 iterations discarded as warmup. Convergence was assessed by examining trace plots, ensuring the potential scale reduction factor was close to 1 for all parameters, and checking for effective sample sizes. A high target average acceptance probability (adapt_delta = 0.95) was used to ensure robust sampling.

3.4. Overall design

Customer heterogeneity is examined along two key dimensions of the booking process. The first dimension is traveler composition, distinguishing between customers traveling with and without babies/children. Prior research shows that traveler composition can affect booking decisions, stay duration, and rate sensitivity, as families are generally more constrained in their choices and planning horizons (Lee & Kim, 2021; Viverit et al., 2023). The second dimension is booking lead time, distinguishing between early and late bookings. Lead time has been shown to influence willingness to pay and intertemporal demand responses, with different implications for pricing and revenue management (Abrate et al., 2019; Arenoe & van der Rest, 2020; Webb et al., 2022). In this study, early bookings are defined as reservations made more than seven days before arrival, while late bookings are those made within seven days, a threshold consistent with industry practice and suitable given the structure of the dataset.

To provide a clear roadmap for the subsequent analysis, the study design proceeds in four stages.

- i. Static model benchmarking (Section 4.1): The behavioral economic model and a traditional loglinear benchmark are estimated for the four hotel-room combinations, allowing for direct model comparison irrespective of time.
- ii. Static group differences (Sections 4.2 and 4.3): Behavioral heterogeneity in demand parameters (Q_0 , α) is tested between families and non-families, and between early and late bookers.
- iii. Dynamic model evaluation (Section 4.4): The analysis is extended to a time-varying context by estimating the TVP-behavioral economic model and comparing it with a TVP-loglinear benchmark. Model performance is further evaluated through checks for potential overfitting between training and forecasting sets and through sensitivity analysis of prior distributions in the Bayesian estimation.

- iv. Dynamic group differences (Sections 4.5 and 4.6): Time-varying demand fundamentals are estimated for the defined customer groups, capturing how baseline demand and price sensitivity evolve dynamically across segments.

4. Results and discussion

4.1. Static demand estimation

To establish a robust foundation for the subsequent temporal modeling, this section compares the performance of the behavioral economic demand model against the conventional loglinear model using the full 26-month booking data. The modeling results were conducted for two room types (A-room and D-room) across both city and resort hotels. This allows us to test whether the behavioral model, which is characterized by its ability to capture nonlinear price-dependent elasticity, offers improved explanatory power in the static cross-sectional dataset. For comparison, a standard loglinear regression model was estimated, which assumes constant elasticity and linear log-transformed relationships between ADR and the average room nights booked.

The key results for each model specification are presented in Table 3. Across all four hotel room types, the behavioral economic model consistently outperformed the static loglinear model in terms of model fit. For instance, for the city hotel A-room, the behavioral specification achieved an adjusted R^2 of 52.47 %, compared to 43.12 % under the loglinear model, and similar performance gaps appear across the remaining cases. Beyond differences in numerical fit, the comparison highlights the analytical value of adopting a behavioral structure. The loglinear specification imposes a constant proportional response to price, producing a monotonic elasticity pattern that overlooks variation in marginal sensitivity across the price range. In contrast, the exponential behavioral model identifies curvature in the demand function, with steeper sensitivity as price increases.

These empirical features align with theoretical expectations that elasticity varies systematically with price rather than remaining constant (Hursh & Silberberg, 2008; Perloff, 2018; Song & Lin, 2023) and are reflected visually in Fig. 1, where the behavioral curves follow the empirical distribution more closely, particularly in the tails. The loglinear model systematically overestimates demand at high prices due to its proportionality constraint, whereas the behavioral specification captures the accelerating decline in demand at elevated price points. Taken together, these results confirm the practical relevance of incorporating behavioral curvature into static demand estimation, providing a more realistic representation of how hotel customers respond to pricing and establishing the behavioral economic model as a more robust and behaviorally grounded tool for applied tourism contexts.

4.2. Group differences: with vs. without babies/children

To further uncover behavioral heterogeneity in hotel demand, this section investigates whether price responsiveness systematically differs between customers traveling with and without babies/children. The first half of Table 4 presents the results of parameter comparison between customer groups in each hotel room type with the Wald test (Fox, 2016).

For the city hotel A-room, the only significant difference is observed in the baseline demand parameter, with non-family customers showing stronger latent demand. However, the price elasticity parameter does not differ significantly, indicating that both groups adjust their booking behavior similarly in response to price. In an urban-oriented market such as the city hotel, this indicates that the basic room category attracts both families and non-families who respond similarly to price changes, with differences arising instead from underlying levels of demand. For practitioners, this implies that demand for entry-level rooms is shaped more by the overall volume of travelers seeking affordable accommodation than by group-specific price responsiveness.

In contrast, for the city hotel D-room, both Q_0 and α differ signifi-

Table 3
Static model results for selected hotel room types: Loglinear vs. behavioral economic model.

	Loglinear model				Behavioral economic model			
	Intercept	Slope	S.E.(10 ⁻²)	R ²	Q ₀	α(10 ⁻⁴)	S.E.(10 ⁻²)	R ²
City hotel								
A-room (N = 153)	1.24 ***	-0.39 ***	10.71	43.12 %	5.01 ***	5.14 ***	9.79	52.47 %
D-room (N = 298)	1.14 ***	-0.31 ***	11.56	28.10 %	5.48 ***	3.19 ***	10.55	40.16 %
Resort hotel								
A-room (N = 187)	1.14 ***	-0.26 ***	10.57	32.24 %	5.90 ***	2.28 ***	10.51	32.97 %
D-room (N = 141)	1.22 ***	-0.29 ***	13.64	24.33 %	6.63 ***	2.32 ***	12.64	35.00 %

Note: ****p* < 0.001.

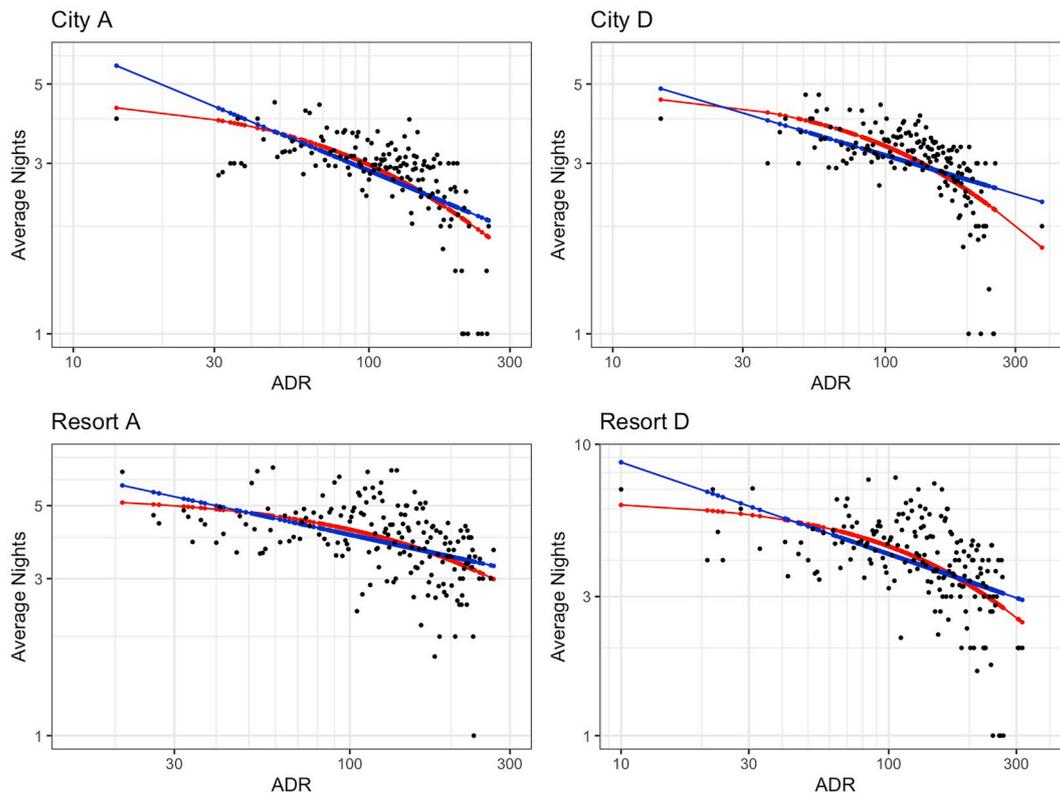


Fig. 1. Static demand curves for selected hotel room types (red curve: behavioral economic model; blue line: loglinear model).

cantly across groups. Families not only exhibit higher baseline demand, but also significantly lower price sensitivity, indicating more inelastic booking behavior. This profile suggests that families may treat the D-room as a necessity, prioritizing the booking despite price increases, likely due to its suitability for group travel. Non-family travelers, by contrast, show more discretionary behavior consistent with flexible booking patterns (Lee & Kim, 2021). From an industry perspective, this highlights the importance of room-category differentiation in urban hotels. Superior-category rooms can be positioned as family-oriented products with reduced reliance on discounting, while revenue management efforts may be more effective when directed at non-family segments.

For the resort hotel, behavioral differences across groups are minimal. Neither baseline demand nor price sensitivity differs for either room type over the 1 % significance level. This general uniformity suggests that family status has limited influence on resort booking behavior. In leisure-oriented markets, shared motivations such as destination appeal, seasonal timing, and holiday scheduling appear to

dominate decision-making, producing a more homogeneous demand structure across customer types. The relatively low sensitivity to price changes also aligns with the notion that resort stays are perceived as planned, commitment-driven consumption rather than discretionary purchases. For practitioners, this indicates that resort demand may be less responsive to fine-grained segmentation by family status, with broader seasonal pricing and capacity management strategies proving more effective.

Overall, this highlights the importance of context-specific segmentation in behavioral demand modeling. In urban contexts, where room-category differences interact with guest composition, disaggregating customer groups is crucial to understanding heterogeneity in demand and refining revenue management strategies. In resort contexts, where destination-driven motivations dominate, pooled models that generalize across customer groups are sufficient to capture demand dynamics.

Table 4
Static model results: With vs. without babies/children and late vs. early booking.

	Q_0			$\alpha(10^{-4})$		
	χ^2	With	Without	χ^2	With	Without
City hotel						
A-room	10.13 ***	5.12 ***	6.81 ***	1.98	6.01 ***	5.53 ***
D-room	6.29 **	5.65 ***	4.82 ***	20.16 ***	4.67 ***	6.20 ***
Resort hotel						
A-room	3.60 *	5.42 ***	6.11 ***	0.85	2.35 ***	2.09 ***
D-room	0.62	5.93 ***	5.60 ***	0.11	2.22 ***	2.32 ***
	χ^2	Late	Early	χ^2	Late	Early
City hotel						
A-room	65.84 ***	2.96 ***	5.49 ***	228.07 ***	10.49 ***	3.79 ***
D-room	86.07 ***	2.81 ***	5.09 ***	236.63 ***	8.29 ***	2.39 ***
Resort hotel						
A-room	302.02 ***	1.84 ***	6.37 ***	527.87 ***	11.26 ***	0.59 *
D-room	134.69 ***	2.00 ***	7.32 ***	342.24 ***	9.49 ***	1.07 ***

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

4.3. Group differences: late vs. early booking

In addition to traveler composition, we further examined behavioral heterogeneity between late and early bookers. The lower panel of Table 4 reports the Wald test results for parameter comparisons between the two groups across hotel–room combinations.

For the city hotel, both baseline demand and price sensitivity differ significantly between late and early bookings. Across both A-room and D-room categories, late bookers show lower baseline demand but higher price elasticity than early bookers, indicating that they are more responsive to price changes. This suggests that late bookers behave in a more price-sensitive and discretionary manner, often searching for last-minute deals or adjusting their booking decisions based on price information closer to the stay date, which aligns with previous findings in hotel booking research (Arenoe & van der Rest, 2020). From a revenue-management perspective, this implies that aggressive late-stage price increases risk deterring these customers, while targeted tactical discounts can be more effective for stimulating late demand, especially in higher-category inventory where advance booking dominates.

For the resort hotel, the differences between late and early bookers are even more pronounced. All room categories exhibit highly significant differences in both parameters, with late bookers consistently displaying lower baseline demand and higher price sensitivity. This result highlights that resort demand closer to the date is relatively fragile and highly price-responsive, potentially reflecting customers who defer booking decisions until confirming availability, weather, or travel arrangements. In such leisure-oriented contexts, last-week discounting may play a critical role in capturing hesitant demand and optimizing occupancy across both standard and premium segments.

The above findings reveal that booking lead time is a key driver of behavioral heterogeneity, with late bookers forming a low-demand, high-price-elastic segment (Webb et al., 2022). This supports the implementation of more cautious late-stage pricing strategies, balancing price increases with the need to stimulate conversions among highly price-sensitive customers.

4.4. Time-varying demand parameters modeling

To evaluate whether the TVP specification improves model fit and forecasting accuracy, an additional comparison was conducted between

the proposed TVP-behavioral economic model and a benchmark TVP-loglinear model. The full 26-month dataset was divided into a training set (first 22 months) and a hold-out test set (last 4 months). Both models were estimated on the training set, and their in-sample training and out-of-sample forecasting performance were evaluated using root mean square error (RMSE) and mean absolute percentage error (MAPE).

As shown in Table 5, the TVP-behavioral economic model consistently achieves lower RMSE and MAPE values than the TVP-loglinear model across almost all hotel–room combinations, both in modeling and forecasting, indicating a more accurate prediction of booking behavior. Importantly, the close alignment between training and forecasting errors indicates that the TVP-behavioral economic model generalizes well and is not prone to overfitting, as excessive overfitting would have resulted in a large increase in out-of-sample errors. The only notable gap appears in the resort A-room case; however, even there, the TVP-behavioral economic model markedly outperforms the TVP-loglinear benchmark, suggesting that any overfitting effect is minimal and does not diminish the model's practical value.

To examine the robustness of prior choices, a sensitivity analysis was conducted following the approach of Assaf et al. (2018). The prior parameters were randomly perturbed, and the model was re-estimated 10 times for each hotel–room combination. Model performance was assessed based on R^2 , RMSE, and MAPE, and the results were compared with those of the reported model. On average, the re-estimated models (with modified priors) delivered nearly identical performance to the reported model. In 73–80 % of the re-estimation runs, the perturbed-prior models outperformed the reported model on at least one of the three metrics (see Table 6). These results confirm that the findings are robust and not overly sensitive to prior choices.

Based on these results, the superiority of the behavioral economic model persists when embedded within a TVP specification, providing stronger explanatory and predictive power than the conventional log-linear alternative. Together with the static comparison in Section 4.1, these findings demonstrate that the behavioral economic model not only captures price-dependent elasticity more effectively but also delivers improved forecasting performance when extended to account for temporal dynamics.

Fig. 2 provides a representative example of the monthly behavioral demand curves used in the longitudinal demand estimation, based on data from the resort hotel D-room. Three months were selected to illustrate distinct seasonal phases: August 2016 (peak), November 2016 (off-peak), and April 2017 (shoulder season). Each scatter plot shows aggregated ADR–night pairs, with the fitted curve representing the demand function estimated for that month. Clear seasonal differences are evident in both the shape of the curve and the distribution of observations.

In August, the curve begins at a high baseline demand level, consistent with stronger latent demand, and bookings cluster around longer stays even as ADR increases. This pattern reflects leisure travelers prioritizing holidays during the peak period, with booking motivation remaining strong despite higher prices. In November, the curve starts at a lower baseline, and bookings concentrate on shorter stays at higher ADR levels, signaling reduced willingness to commit to longer trips and greater caution in discretionary spending. April presents an intermediate profile, with moderate Q_0 and a more dispersed spread of bookings across ADR and stay length, consistent with transitional travel patterns in the shoulder season.

Rather than uniform price sensitivity, the results demonstrate that customers' willingness to commit to both price levels and length of stay is seasonally contingent. For hotel managers, this highlights the need to adapt revenue management and stay-length controls dynamically. For example, adopting minimum-stay requirements and higher rates during peak months, while emphasizing flexible offers and shorter-stay promotions in off-peak periods. This example illustrates the value of the TVP-behavioral economic model in capturing structural seasonal shifts in both booking motivation and stay-length patterns over time,

Table 5
Training and forecasting performance: TVP-loglinear vs. TVP-behavioral economic models.

	TVP-loglinear model				TVP-behavioral economic model			
	Training		Forecasting		Training		Forecasting	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
City hotel								
A-room	0.139	0.255	0.146	0.227	0.136	0.254	0.143	0.232
D-room	0.149	0.262	0.140	0.245	0.147	0.259	0.140	0.240
Resort hotel								
A-room	0.187	0.339	0.357	1.804	0.187	0.332	0.264	0.560
D-room	0.203	0.340	0.384	1.603	0.218	0.701	0.334	0.784

Table 6
Sensitivity analysis for Bayesian TVP-behavioral economic model under perturbed priors.

	Bayesian R^2	RMSE	MAPE
Reported model	31.13 %	1.32	0.35
Re-estimated models with perturbed priors	31.24 %	1.33	0.35
Frequency of better performance	73.00 %	78.00 %	80.00 %

providing a more responsive tool for managing demand than static behavioral models.

4.5. Behavioral dynamics in groups: with vs. without babies/children

A full summary of the time-varying estimation is presented in Table 7, with the monthly changes of Q_0 and α visualized in Fig. 3. For the city hotel A-room, the Q_0 values for customers with babies/children remain consistently high across months, showing only minor seasonal movement. This points to a stable and predictable baseline demand, reflecting families' tendency to plan urban stays around fixed needs such as childcare or school holidays. The corresponding α line remains relatively flat, consistent with less elastic demand and limited reactivity to price throughout the year. In contrast, for non-families, both Q_0 and α fluctuate more noticeably. Baseline demand dips during low-travel months (November to January) and rises during summer and spring breaks, while price elasticity increases in off-peak periods and declines in high-demand months. This indicates a more price-sensitive group that adapts booking behavior dynamically to seasonal opportunities,

consistent with discretionary and flexible travel motivations (Viverit et al., 2023).

The city hotel D-room shows a similar division. Among family travelers, Q_0 remains high and stable across months, suggesting strong and structured demand for superior rooms that are better suited to group travel. Elasticity also follows a seasonal rhythm but with limited reactivity overall, reflecting calendar-driven, necessity-oriented family trips. Customers without babies/children again display more pronounced responsiveness. Their baseline demand oscillates sharply, with troughs in winter and peaks in summer, while α follows an inverse seasonal trend, with greater elasticity in low-demand months and more inelastic booking during peak periods. For operators, this indicates that non-family segments in urban hotels actively respond to seasonal price signals, adjusting booking timing and room choice based on perceived value and availability, whereas family segments provide a steadier and less price-sensitive base.

Compared to the more stable behavioral patterns in city hotels, the resort hotel demand exhibits stronger seasonal variation, particularly in price sensitivity. For the A-room, baseline demand remains consistently high and steady across months, underscoring its alignment with core leisure preferences and its role as an accessible, reliable option for resort stays. However, elasticity fluctuates considerably: price sensitivity increases in low-demand months but declines in peak seasons, implying that while interest in this category is stable, willingness to pay varies with seasonal travel intensity. In contrast, the D-room displays both higher volatility and a rising trend in Q_0 , suggesting growing demand for superior-category resort rooms. This is paired with unstable and seasonally reactive α values, with greater price elasticity in off-peak

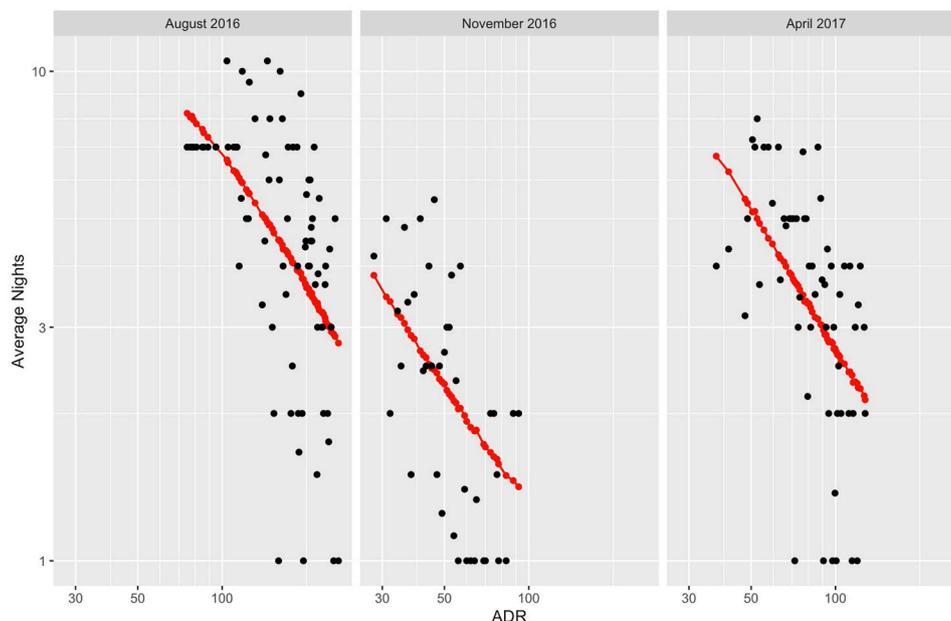


Fig. 2. Monthly dynamic demand curves for resort hotel D-room.

Table 7
TVP-behavioral economic model results for customer groups with different demand patterns.

	Q_0			$\alpha(10^{-4})$			Bayesian R^2
	Mean	S.D.	[Min, Max]	Mean	S.D.	[Min, Max]	
City hotel, A-room							
With babies/children	9.79	2.07	[5.86, 11.97]	7.25	1.07	[5.36, 9.43]	19.64 %
Without babies/children	6.15	0.90	[4.51, 7.47]	7.75	1.83	[4.72, 11.00]	24.65 %
City hotel, D-room							
With babies/children	9.01	1.38	[5.71, 10.47]	7.41	0.97	[5.82, 9.16]	13.85 %
Without babies/children	7.36	1.30	[5.16, 9.67]	6.00	1.48	[4.09, 9.12]	27.04 %
Resort hotel, A-room	11.66	0.33	[8.67, 14.67]	9.61	0.99	[2.76, 17.70]	42.37 %
Resort hotel, D-room	15.40	6.17	[3.31, 24.56]	6.83	4.05	[2.01, 16.97]	32.84 %
City hotel, A-room							
Late booking	3.68	0.84	[2.13, 5.53]	10.34	2.40	[8.53, 12.18]	23.32 %
Early booking	10.34	0.99	[5.64, 21.53]	6.74	6.00	[4.40, 9.15]	24.64 %
City hotel, D-room							
Late booking	6.10	0.91	[4.15, 8.23]	15.18	5.80	[6.44, 22.31]	17.08 %
Early booking	6.55	0.79	[4.48, 8.18]	5.05	2.20	[3.41, 6.75]	21.50 %
Resort hotel, A-room							
Late booking	3.50	1.01	[1.54, 4.81]	20.38	8.90	[1.99, 29.01]	15.47 %
Early booking	16.64	0.96	[8.03, 21.52]	6.78	3.00	[2.05, 12.13]	26.77 %
Resort hotel, D-room							
Late booking	4.90	1.87	[4.41, 5.30]	39.66	8.30	[9.22, 54.67]	11.61 %
Early booking	22.78	0.97	[11.32, 28.65]	6.26	2.90	[1.73, 14.81]	40.48 %

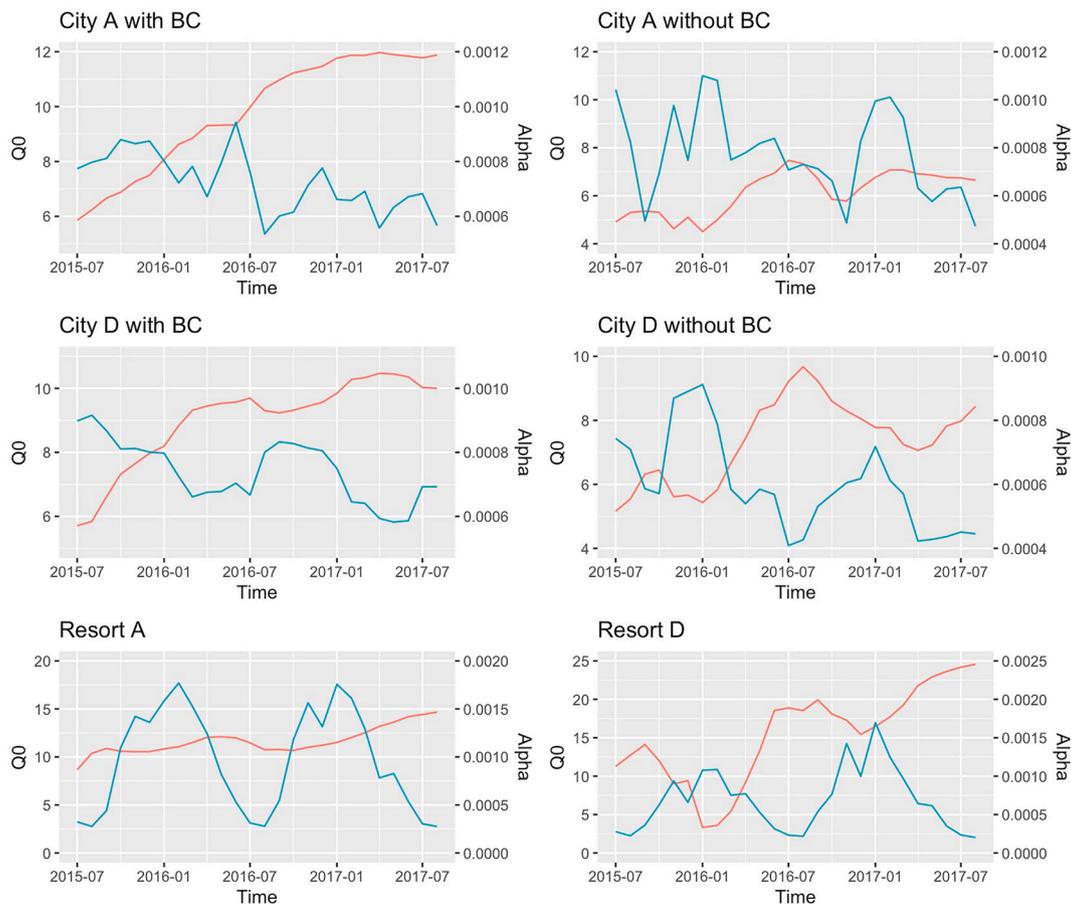


Fig. 3. Time-varying behavioral demand parameters by traveler composition (red lines indicate the estimated Q_0 , teal lines indicate the estimated α , BC: babies/children).

periods but reduced sensitivity in high-occupancy months. The D-room therefore caters to a more diverse demand base, serving both price-sensitive off-season travelers and higher-paying peak-season customers.

4.6. Behavioral dynamics in groups: late vs. early booking

Fig. 4 also illustrates the time-varying patterns of baseline demand and price elasticity for late and early bookings, with summary statistics presented in Table 7. The results reveal that booking lead time is associated with distinct temporal dynamics rather than simply level

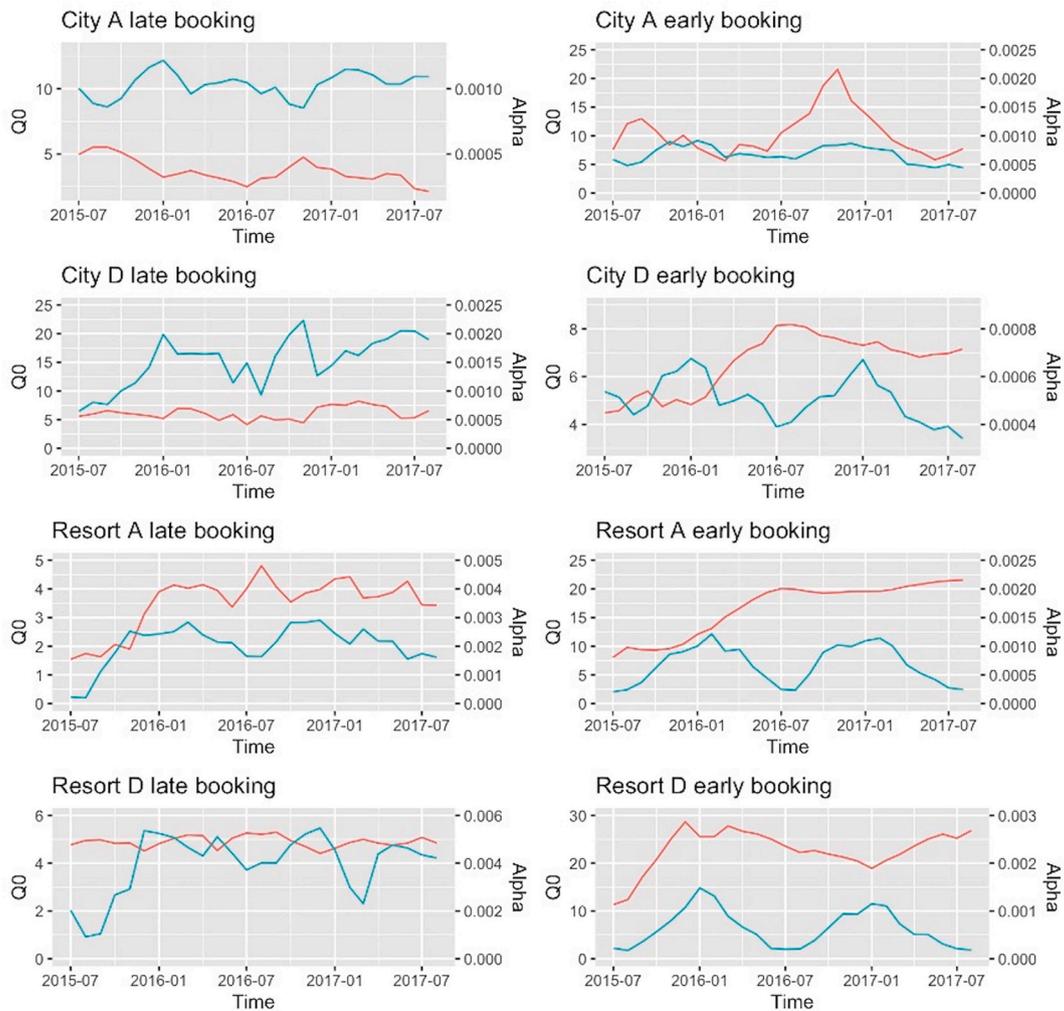


Fig. 4. Time-varying behavioral demand parameters by booking pattern (red lines indicate the estimated Q_0 , teal lines indicate the estimated α).

differences.

For the city hotel A-room, both booking groups display relatively stable Q_0 and α values over time, with only mild seasonal fluctuations. The key difference is that early bookers maintain higher baseline demand, reflecting more committed customers who plan ahead for standard rooms, while late bookers remain somewhat more price sensitive, consistent with opportunistic demand for lower-tier inventory. A temporary spike in early bookers' baseline demand may be linked to a specific event period that increased advance commitments and elevated the volume of early reservations.

The city hotel D-room shows a sharper division between booking groups, underscoring the different roles of higher-tier rooms in urban markets. For late bookers, baseline demand remains consistently low and flat, indicating a relatively small, steady market of opportunistic purchasers for premium rooms close to arrival. Early bookers, by contrast, exhibit a seasonal pattern with a gradual upward trend in Q_0 , peaking in high-demand months, coupled with a decline in price elasticity. This indicates that premium-category rooms are secured earlier in peak seasons by customers who are less price sensitive and more motivated by availability and suitability. Late bookers display more volatile elasticity across the year, with particularly high responsiveness in off-peak months, suggesting that premium rooms are then treated as discretionary upgrades when attractive prices are available.

The resort hotel exhibits stronger seasonal dynamics overall, consistent with the leisure-driven context. In both A- and D-room categories, early bookers show clear and regular seasonality in both Q_0 and

α : baseline demand peaks during holiday periods and price sensitivity declines, reflecting the planned and necessity-driven nature of peak-season resort travel. Late bookers, in contrast, display relatively flat Q_0 profiles with limited seasonal response, though their price elasticity still fluctuates. This indicates that in resorts, late demand is smaller and more opportunistic, driven primarily by price signals rather than by seasonal travel patterns. Importantly, the resort D-room category shows greater variability, highlighting its appeal to both committed, high-value travelers during peak periods and opportunistic, price-sensitive customers in off-peak months. This dual profile underlines the commercial importance of superior-category resort rooms as flexible revenue drivers across market conditions.

5. Conclusions

5.1. Summary of findings

The empirical analysis confirms that the behavioral economic model provides a superior fit compared to the traditional loglinear benchmark, both in static and time-varying contexts. Static estimations highlight notable heterogeneity across customer groups in the city hotel. Families traveling with babies/children exhibit higher baseline demand and lower price sensitivity for superior-category rooms, suggesting more necessity-driven, less price-elastic booking behavior. Non-family travelers show weaker intrinsic demand and greater price responsiveness, reflecting more discretionary booking patterns. In the resort hotel,

customer composition plays a smaller role with demand appearing more uniform across groups, consistent with leisure-oriented motivations such as holiday timing and destination appeal that reduce segmentation effects. Booking lead time also emerges as an important dimension of heterogeneity. Across both hotels, late bookers consistently show lower baseline demand and higher price sensitivity, while early bookers maintain stronger baseline motivation and reduced elasticity, particularly during peak periods. This pattern underscores the discretionary and price-sensitive nature of last-minute demand versus the more stable and committed demand of early planners.

Extending the model to a time-varying framework reveals systematic temporal dynamics. Seasonal fluctuations are especially pronounced in resort hotels, where demand becomes more inelastic and baseline motivation rises during peak holiday periods, while off-peak months are characterized by suppressed demand and heightened sensitivity to price. These effects are most visible in resort D-rooms, which combine a rising long-term demand trend with strong monthly variability, reflecting their appeal to both high-value peak-season travelers and more price-sensitive off-season guests. In contrast, the city hotel exhibits more moderate temporal shifts, with variations largely shaped by differences in customer mix rather than sharp seasonal swings.

These findings affirm that hotel demand is shaped by both structural heterogeneity and temporal heterogeneity (Boto-García et al., 2021; Parrilla et al., 2007). The TVP-behavioral economic model effectively captures these dual layers of variation, offering a more realistic and actionable representation of consumer demand than static or purely linear approaches.

5.2. Theoretical and methodological implications

Although classical demand theory recognizes that elasticity can vary across price ranges and over time, these dynamics are typically treated abstractly and rarely operationalized in empirical tourism research. By embedding a behavioral economic demand model within a TVP framework, this study advances theory by demonstrating that fluctuations in baseline demand and price sensitivity are systematic, measurable, and closely aligned with behavioral constructs.

The observed time-varying effects can be directly linked to established behavioral theories. The seasonal movements of demand curvatures and elasticity dynamics are theoretically consistent with reference-dependent preference formation, in the sense that willingness to pay is known to change with expectations that vary across peak and off-peak periods, although the present study does not attempt to identify reference price effects causally. These dynamics further resonate with the concept of state-dependent preferences, which emphasizes that valuations evolve with contextual and temporal states rather than remaining static (Lin et al., 2023). By empirically capturing these dynamics, this study provides one of the first operationalizations of such theoretical constructs in a real-world hospitality setting.

Methodologically, the research demonstrates that behavioral demand models can be extended beyond static estimation to capture temporal heterogeneity. The model consistently outperformed the log-linear benchmark in both static and dynamic contexts, confirming that price responsiveness is nonlinear and evolves with market conditions. Importantly, the framework enables disentangling structural heterogeneity (families vs. non-families, early vs. late bookers) from temporal heterogeneity (peak vs. off-peak). This dual-layered perspective refines theoretical understanding of tourism demand by showing how commitment-driven and discretionary consumption coexist and vary across time. In doing so, the study enriches the empirical toolkit of tourism demand analysis and provides a transferable methodological template for future applications involving richer datasets or contexts affected by external shocks.

5.3. Practical implications

Managerially, the findings demonstrate that the TVP-behavioral economic framework can be operationalized to support segmentation, pricing, and marketing strategies that adapt to both structural and temporal variations in demand. For instance, families booking superior-category rooms exhibit consistently high baseline demand and low price sensitivity, indicating that upselling and value-added offers (e.g., bundled meals, family amenities) may be more effective than discounting. Non-family travelers, particularly in city hotels, show lower baseline demand and heightened elasticity, especially in off-peak periods, suggesting that targeted promotions, flexible booking conditions, or short-stay discounts are more suitable. Similarly, early bookers provide a stable demand base with lower price sensitivity, whereas late bookers represent a smaller, highly price-responsive segment that requires more tactical interventions, particularly in low-demand months.

The time-varying results also highlight how demand dynamics align with policy contexts. Seasonal fluctuations in elasticity mirror existing interventions in tourism markets. Off-season subsidies, cultural programming, and promotional campaigns (Figini & Vici, 2012; Senyao et al., 2021) address high-elasticity, low-demand periods, while measures such as tourist taxes, minimum-stay regulations, or demand caps during overtourism episodes (Butler & Dodds, 2022; Seraphin & Ivanov, 2020) are supported by the finding that demand is less price-sensitive in peak seasons. By capturing these patterns explicitly, the model provides a more behaviorally grounded evidence base for policy design.

Beyond hotel operations, the framework complements emerging AI-driven revenue management systems by embedding behavioral interpretability into dynamic data fitting. Whereas algorithmic tools may predict demand mechanically, the TVP-behavioral economic model explains why responsiveness shifts across time and groups, allowing managers to anticipate discretionary versus necessity-driven behavior. The model also offers a foundation for resilience planning. In contexts of shocks such as pandemics, geopolitical instability, or climate disruptions, tracking the evolution of elasticity and baseline demand could help managers and policymakers anticipate when demand is likely to collapse or rebound.

5.4. Limitations and future research

This study is subject to several limitations that should be considered when interpreting the findings. First, limited hotel and room information restricts empirical segmentation. The empirical analysis relies on an open-access dataset that covers only two Portuguese hotels. Although this provides a useful contrast between an urban and a leisure-oriented context, the restricted geographic scope and anonymized room classifications reduce the ability to generalize findings across different hotel types, brands, or regions. Similarly, segmentation is limited to a binary distinction between bookings with and without babies/children, which, while revealing important behavioral differences, does not capture broader demographic or psychographic diversity. Given the validity of this modeling framework, future applications to richer datasets, such as those held by hotel managers or industry partners, have the potential to generate richer insights into customer heterogeneity, marketing responses, and the like.

Second, the limited time horizon does not include special events. The dataset spans July 2015 to August 2017, a period that, while sufficient for testing the framework, does not encompass major crises, policy interventions, or other extraordinary events that typically shape tourism demand. As a result, the current analysis cannot demonstrate how the time-varying behavioral model performs under conditions of structural shocks or policy-driven market adjustments. Nonetheless, the framework is designed to accommodate temporal fluctuations and evolving relationships. Future research should therefore extend the temporal scope to cover longer horizons and incorporate special events to fully demonstrate the capacity of the model to capture dynamic, context-

dependent behavior.

Third, due to the fact that the available booking dataset does not include non-price attributes (e.g., service quality indicators, facility ratings) or competing hotels' pricing strategies, the present model focuses on the own prices only. The two hotels in our sample are located in different cities and operate in distinct markets, meaning that cross-price competition or substitution cannot be modeled. As a result, integrating non-price demand determinants or competitor pricing into the TVP framework is not empirically feasible with this dataset. Nonetheless, the limitations to observable attributes do not affect the internal validity of the behavioral demand estimates, because the TVP formulation captures temporal heterogeneity within each hotel's own price–demand relationship. Future work could extend the model by incorporating non-price attributes and competition effects in multi-property datasets that contain explicit cross-price substitution information.

CRedit authorship contribution statement

Gabrielle Lin: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Xinyang Liu:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Jason Li Chen:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis.

Impact statement

This research delivers a novel analytical tool that enhances how the tourism and hospitality industries understand and respond to consumer behavior. By integrating behavioral economics with time-varying parameter modeling, the study captures how hotel demand dynamically shifts in response to pricing changes, structural heterogeneity, and seasonal trends. The demonstrable impact of this work lies in its real-world application: hotel operators can adopt this model to implement more precise and flexible pricing strategies, maximize revenue through informed yield management, and tailor services to distinct customer segments. Moreover, the ability to anticipate demand fluctuations over time supports more efficient staffing, inventory control, and sustainability planning. By offering an evidence-based, interpretable approach to dynamic demand management, the study contributes to more resilient, responsive, and equitable tourism and hospitality systems, ultimately supporting economic recovery, service quality, and consumer well-being in a volatile global tourism environment.

Declarations of competing interest

None.

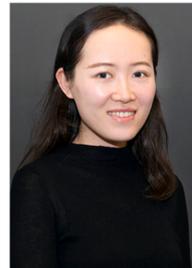
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