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Research Article

BEYOND PRICE: HOW PLATFORM POWER SHAPES DEMAND ALLOCATION IN ONLINE HOTEL CHANNELS

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Abstract

Rate disparity remains a widely used but poorly understood pricing strategy in the hotel industry. While previous research generally assumes that lower prices shift demand toward less expensive channels, this study investigates whether such effects occur in practice. Using high-frequency booking and pricing data from five full-service hotels across multiple online travel agencies (OTAs), we analyze how rate disparity relates to the distribution of demand across channels. The findings show that the impact of price differences is limited, highly non-linear, and strongly dependent on contextual factors. Channel market power and hotel-specific characteristics seem to play a more significant role than price advantages under the observed conditions. Rate disparity reallocates demand across channels rather than increasing total demand within the sample studied, and its effectiveness varies across demand seasons and competitive environments. These results challenge the prevailing focus on price-based competition and suggest that platform dynamics and hotel attributes may play a more central role in distribution outcomes.

Keywords: hotel revenue management, rate disparity, distribution channel, competitive dynamics, pricing strategy

JEL Classification: L14, L83, M47

1. Introduction

The rapid growth of online travel agencies (OTAs) has fundamentally transformed hotel distribution, creating a complex, multichannel environment where pricing strategies are highly visible and intensely competitive (Bilgihan & Nejad, 2015; Maier, 2013). In this context, rate parity, the practice of maintaining consistent prices across channels (Gazzoli et al., 2008), has long been promoted as a mechanism to ensure fairness and protect brand value (Choi & Kimes, 2002; Ling, 2023). However, both hotels and OTAs frequently deviate from parity by offering lower prices on selected channels, resulting in rate disparity (Ling et al., 2022; Ling, 2024). These practices are often justified by the expectation that price differences will shift demand toward lower-priced channels and ultimately improve revenue performance.

Despite its widespread use, the effectiveness of rate disparity remains unclear. Existing research and industry logic largely rely on standard economic intuition: lower prices should attract demand (Enz et al., 2016). However, this assumption may be overly simplistic in a platform-mediated environment where consumers compare prices across channels, and where distribution outcomes are shaped not only by price but also by platform visibility, loyalty programs, and market power (Bamberger &Lobel, 2017). In such settings, the relationship between price differences and demand allocation may be non-linear, context-dependent, and potentially weak.

Most discussions of rate disparity focus on its ability to shift demand across channels (Kim et al., 2020; Ling et al., 2025), implicitly treating all bookings as equally valuable. However, from a hotel managerial perspective, distribution channels differ significantly in their economic implications. OTAs charge varying levels of commission, and hotels incur different costs depending on the channel through which a booking is made (Ling et al., 2022). As a result, reallocating demand across channels, even without increasing total bookings, can materially affect profitability. A shift toward a lower-priced channel does not necessarily improve financial performance if that channel is associated with higher distribution costs. Conversely, directing demand toward more cost-efficient channels may enhance profitability (Anderson et al., 1997) even in the absence of price advantages.

This perspective suggests that the effectiveness of rate disparity cannot be evaluated solely in terms of demand redistribution. Instead, it must be understood within a broader system in which pricing decisions interact with channel characteristics, platform power, and cost structures. Understanding how rate disparity reshapes the distribution of demand across channels is therefore a necessary step toward evaluating its strategic and financial implications.

This study revisits the effectiveness of rate disparity by focusing on how it operates in practice. Rather than examining aggregate outcomes, we analyze high-frequency booking and pricing data to understand how demand is redistributed across channels under varying levels of price difference. Using longitudinal data from five full-service hotels operating across multiple OTAs, we investigate whether lower prices systematically translate into greater demand and, if so, under what conditions.

Our findings suggest that rate disparity does not function as a simple price-demand lever. While price differences have some predictive power, their effects are modest and highly contingent on contextual factors. Channel market power and hotel-specific characteristics consistently play a more prominent role in determining demand allocation than price alone. Moreover, the impact of rate disparity varies across demand conditions, indicating that its effectiveness is shaped by both competitive dynamics and seasonal factors. Importantly, the results indicate that rate disparity primarily redistributes demand across channels rather than increasing total demand.

By highlighting the limited and context-dependent role of price differences, this study contributes to a more nuanced understanding of pricing in platform-based distribution systems. It suggests that the industry's emphasis on rate disparity as a primary competitive tool may be overstated and that greater attention should be given to the structural characteristics of distribution channels and hotel attributes. For practitioners, the findings underscore the need to move beyond price-focused strategies and consider both the competitive and economic implications of channel choice in multi-channel environments.

2. Literature review

2.1 Rate parity, rate disparity and consumer response

Rate parity, defined as the practice of maintaining consistent prices across distribution channels, has traditionally been justified as a way to ensure price fairness and protect brand value (Choi & Mattila, 2009; Gazzoli et al., 2008). When prices are consistent, consumers are less likely to question whether they are receiving a fair deal, which reduces search costs and reinforces trust in both the hotel and the booking channel (Sipic & Zavisic, 2018). In these circumstances, channel choice is expected to depend less on price and more on non-price attributes such as convenience, familiarity, and service quality (Múgica & Berné, 2019).

In contrast, rate disparity creates visible price differences across channels, which may encourage comparison behaviour and increase price sensitivity (Law et al., 2007; Noble et al., 2005). From a standard economic perspective, lower prices should attract demand, suggesting that channels offering discounted rates can capture a greater share of bookings. Empirical and survey-based studies support the view that online hotel consumers frequently compare prices across platforms and display strong price sensitivity (Kim et al., 2006; Liu & Zhang, 2014; Schoenbachler & Gordon, 2002).

However, this reasoning implicitly assumes that price is the dominant factor in channel choice. In digital environments with high transparency and low switching costs, consumers may respond to price differences, but such responses may not translate into substantial or consistent shifts in booking behavior. Other factors, such as brand perception, trust, and prior experience, can moderate or even outweigh the association with price. Notably, much of the existing evidence supporting these assumptions is derived from experimental, survey-based, or conceptual studies, which means that the mechanisms they propose have seldom been tested against real hotel operational data. This reliance on non-operational data may lead to an incomplete or overly stylized understanding of how consumers behave across channels. Moreover, exposure to rate disparity may alter consumers' perceived value and willingness to pay, potentially weakening the intended effect of price reductions (Sharma & Nicolau, 2019).

Taken together, previous literature suggests that while rate disparity is related to consumer behavior, its effects are likely to be conditional rather than universal. This raises an important question: to what extent does rate disparity meaningfully shift demand in real-world multi-channel environments?

2.2 Platform power and channel competition in OTA markets

The emergence of OTAs has introduced a platform-mediated structure to hotel distribution, where a small number of dominant intermediaries control access to large pools of demand. In these markets, competition is not limited to price but is shaped by platform characteristics, including visibility, ranking algorithms, user base size, and loyalty ecosystems (Nuccio & Guerzoni, 2019; Smith & Telang, 2016).

Platform dominance can create asymmetric competitive conditions across channels. Leading OTAs often benefit from strong brand recognition, habitual usage, and extensive customer data, which allow them to influence consumer choice beyond price considerations (Wu et al., 2021). As a result, smaller or less dominant channels may find it difficult to capture demand even when offering lower prices.

This dynamic is particularly evident in markets characterized by a dominant OTA. In China, for instance, leading platforms such as Ctrip have historically shaped competitive behavior among both hotels and rival intermediaries (Shao & Kenney, 2018). Competing OTAs may engage in price reductions, often by sacrificing commissions (Toh et al., 2011), to attract price-sensitive consumers, while hotels may strategically support alternative channels to counterbalance dominant players. These interactions reflect a broader platform competition in which price is only one of several strategic levers.

Beyond differences in market power, distribution channels also vary in their economic implications for hotels. OTAs typically charge commissions that can differ significantly across platforms, while other channels may involve lower marginal costs (O'Connor & Frew, 2004). Previous research has highlighted the importance of distribution costs in shaping channel strategies and profitability, particularly in the context of OTA dependence and disintermediation efforts (Gazzoli et al., 2008). However, relatively little attention has been paid to how pricing practices such as rate disparity interact with these cost differences. As a result, shifts in demand across channels induced by price differences may have uneven profitability consequences, depending on the relative cost of each channel. This underscores the need to consider not only demand allocation but also the economic value of that allocation across distribution channels.

2.3 Demand allocation across channels: beyond the law of demand

Traditional economic theory predicts that a decrease in price leads to an increase in quantity demanded, ceteris paribus (Varian, 2019, pp. 30–32). Applied to multi-channel distribution, this logic implies that lower prices for a certain hotel on a given channel should increase the total quantity of room nights demanded for that hotel. However, in practice, hotels' inventory is distributed across multiple intermediaries, meaning that price changes may affect where bookings occur rather than just how many bookings are generated. This "cannibalism" could happen when consumers who have already decided to book a specific hotel may simply choose the channel offering the lowest price, leading to shifts in channel-level market shares rather than changes in total demand. The distinction between demand generation and demand redistribution is critical for operations and is a focal point of this study.

At the same time, demand allocation is influenced by a range of contextual factors beyond price. Hotel-specific attributes, such as brand strength, location, and service quality, shape baseline demand and consumer preferences (Garrow et al., 2006). Similarly, channel-level characteristics, including user experience and perceived reliability, affect booking decisions. These factors may interact with price differences in complex and potentially non-linear ways, limiting the predictive power of simple price-based models. Consumer heterogeneity further complicates this relationship. Some consumers actively compare prices across channels, while others display habitual booking *behavior* and remain loyal to specific platforms (Fournier, 1998; Reichheld & Sasser, 1990). Consequently, the same level of rate disparity may lead to different outcomes depending on the composition of demand.

2.4 Seasonality and strategic use of rate disparity

The effectiveness of pricing strategies in hospitality is closely linked to demand conditions. During high-demand periods, hotels often face capacity constraints and may rely less on price-based competition, as rooms can be sold without aggressive discounting (Kimes, 1989, Talluri & van Ryzin, 2004, pp. 5–8). In contrast, during low-demand periods, price reductions may be used more actively to stimulate bookings and improve occupancy.

In a multi-channel context, seasonality may also be associated with how rate disparity is deployed and how effective it is. OTAs and hotels may be more willing to engage in price competition during low-demand periods, using lower prices to attract incremental demand or shift bookings across channels. Conversely, in high-demand periods, the marginal benefit of offering lower prices may diminish.

However, the interaction between seasonality and rate disparity is likely to be complex. Changes in demand conditions affect not only pricing behavior but also channel strategies, inventory allocation, and competitive dynamics. This suggests that the effectiveness of rate disparity should be understood as contingent on both price levels and the broader demand environment.

2.5. Summary and research gap

The existing literature offers valuable insights into rate parity, consumer price sensitivity, and OTA competition. However, it tends to emphasize price as the primary driver of demand, often overlooking the complex interactions between pricing, platform power, and contextual factors. Additionally, while prior studies acknowledge differences in channel costs, limited attention has been given to how pricing strategies such as rate disparity may indirectly influence profitability through their effect on demand allocation across channels.

This study addresses these gaps by examining how rate disparity is linked to the distribution of demand across channels, considering platform dominance, hotel heterogeneity, and demand seasonality. Rather than assuming a direct and linear relationship between price and demand, we investigate the conditions under which rate disparity meaningfully affects booking patterns. In doing so, we offer a more nuanced understanding of pricing effectiveness in platform-based hotel distribution systems and highlight its broader managerial implications.

3. Methodology

3.1 Data and research context

This study uses high-frequency panel data capturing daily pricing and booking activity across multiple online distribution channels. The dataset consists of 621 hotel-day observations contributed by five full-service, five-star chain hotels located in three cities in China, generating more than 36,000 room-nights booked. These hotel-day observations represent the total number of daily pricing and booking records provided by the five properties, rather than a continuous sequence of calendar days. For each hotel, we observe daily room rates across multiple online travel agencies (OTAs), as well as the corresponding number of rooms booked through each channel.

The empirical setting reflects a platform-mediated distribution environment in which hotels simultaneously list inventory across several intermediaries with differing levels of market power. Consistent with industry practice, hotels maintain a presence on both dominant and secondary OTAs, creating variation in visibility, demand access, and competitive positioning across channels. This structure allows us to observe how differences in relative pricing across channels are associated with the allocation of bookings.

Rather than relying on cross-sectional comparisons across many properties, the research design leverages within-hotel and within-channel variation over time. This approach enables us to examine how changes in relative prices relate to shifts in demand allocation under comparable contextual conditions. By focusing on temporal variation within the same hotels, we mitigate concerns about unobserved heterogeneity in hotel quality, brand positioning, and location.

While the number of hotels is limited, the dataset provides a detailed view of real-world pricing and booking behavior over an extended period. The multi-city context, chain-brand consistency, and the depth of hotel-day observations across properties support the analytical relevance of the findings for understanding underlying behavioral mechanisms in multi-channel distribution settings.

3.2 Measurement of rate disparity and demand allocation

To capture differences in pricing across distribution channels, we first construct a Rate Disparity Index (RDI) that captures, for each hotel and stay date, the percentage gap between the highest and lowest OTA prices for the same booking conditions, reflecting the extent to which the lowest-priced channel deviates from the highest-priced channel on that day. Beyond the RDI, we also compute pairwise price comparisons by expressing each channel's price as a ratio to the lowest-priced channel, providing a consistent measure of how each channel is positioned relative to the lowest available rate.

Rate parity is defined using a threshold-based approach. Consistent with industry practices and prior research (e.g., Gazzoli et al., 2008), prices within ±2% of the average are considered parity, while larger deviations are classified as disparity. Price information is standardized across channels: it is collected two days prior to the stay date (a window that aligns with the booking patterns), reflects hotel-supplied (not third-party) prices, corresponds to the lowest selling price for a one-night stay in the entry-level or lowest available room type, and excludes any coupons or cash-back benefits. Importantly, the RDI is interpreted not merely as a price difference but as a proxy for strategic price positioning across channels, capturing the extent to which hotels (or intermediaries) deviate from parity in ways that correspond to differences in demand allocation.

3.3 Demand allocation

The primary dependent variable reflects the distribution of demand across channels, not total demand. For each hotel-day-channel observation, we compute the proportion of total rooms booked through a given channel relative to the total room-nights booked across all observed OTA channels on that day. This share represents the channel's contribution and serves as the basis for assessing how demand is allocated across competing distribution channels.

We refer to this share as market penetration, which captures the extent to which each channel secures bookings within the observed competitive set. This measure provides a direct indication of channel strength and helps explain how platform power influences the allocation of demand across distribution channels.

3.4 Control variables

To account for contextual factors that may influence booking behavior, we include several control variables. First, demand conditions are controlled by categorizing days into low, medium, and high demand periods based on the distribution of total bookings. This approach captures seasonal and cyclical variation in demand while maintaining consistency across hotels.

Second, hotel-level controls are introduced to account for differences in baseline demand and customer preferences. These controls capture time-invariant characteristics such as brand positioning, service level, and location, which may influence channel choice independently of price. Third, we incorporate channel-level indicators to reflect differences in platform characteristics, including relative market presence and usage patterns. These variables help capture the role of platform-specific factors beyond pricing. Together, these controls isolate the relationship between rate disparity and demand allocation while accounting for key sources of variation in the data.

3.5 Empirical strategy

The empirical analysis examines the relationship between rate disparity and demand allocation using regression-based models applied to panel data. The models are designed to capture both linear and non-linear associations between pricing differences and booking outcomes.

Given the potential for diminishing or threshold effects, polynomial terms of the Rate Disparity Index were included to allow for non-linear relationships. This approach informs whether small price differences have limited impact while larger disparities produce stronger effects, or whether the relationship is asymmetric depending on whether a channel is priced above or below the average.

To account for unobserved heterogeneity, hotel-level fixed effects are used to control for time-invariant characteristics specific to each property. This specification ensures that estimated relationships are driven by within-hotel variation rather than cross-hotel differences. Furthermore, standard errors are adjusted for clustering at the hotel level to account for serial correlation within properties over time.

Importantly, the empirical strategy is designed to identify associations rather than causal effects. While the use of within-hotel variation strengthens internal validity, the observational nature of the data does not allow for definitive causal inference. Instead, the analysis focuses on uncovering consistent patterns and conditional relationships that characterize how rate disparity operates in practice.

3.6 Scope and interpretation

This study examines demand allocation across distribution channels, rather than total demand generation or profitability outcomes. although distribution channels differ in their cost structures and commission levels; direct measures of channel-specific profitability are not observed in the data. As a result, the analysis does not test the financial impact of rate disparity. However, shifts in demand across channels have important economic implications. Because channels vary in their cost to the hotel, changes in the distribution of bookings may translate into differences in profitability even when total demand remains unchanged.

The results of this study should thus be interpreted as identifying the behavioral patterns through which such effects may arise. By focusing on high-frequency variation in real-world pricing and booking behavior, the methodology provides a detailed view of how rate disparity is associated with demand allocation in a platform-mediated environment. This approach complements previous research based on aggregate or experimental data by offering insight into the micro-level dynamics of multi-channel distribution.

4. Results

4.1 Descriptive statistics and channel structure

The analysis begins by examining the distribution of bookings across channels. As shown in Table 1, the channels were sorted in an ascending order of market share, and the distribution of room nights is highly concentrated. The dominant channel (Channel 6, Ctrip) accounts for approximately 70.54% of total bookings across the five sample hotels, while the remaining channels contribute substantially smaller shares (0.23%, 0.42%, 0.88%, 6.96%, and 20.96%, respectively).

Table 1. OTA penetration rates among sample hotels

Hotel	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5	Channel 6	Total
1	0.10%	0.15%	0.54%	3.28%	17.73%	78.21%	100%
2	0.00%	0.11%	0.86%	12.72%	29.89%	56.42%	100%
3	0.00%	0.14%	0.14%	6.22%	20.55%	72.95%	100%
4	1.02%	1.52%	1.56%	4.10%	12.91%	78.88%	100%
5	0.00%	0.98%	2.07%	2.93%	4.13%	89.89%	100%
Total	**0.23%**	**0.42%**	**0.88%**	**6.96%**	**20.96%**	**70.54%**	**100%**

Source: Own creation

This distribution indicates a strong asymmetry in market power across channels, with one dominant platform capturing most of the demand. Such concentration provides an important context for interpreting the role of pricing: if price were the primary driver of demand allocation, lower-priced channels would be expected to capture larger shares. Instead, the observed structure suggests that baseline platform preference and channel dominance may constrain the impact of price differences.

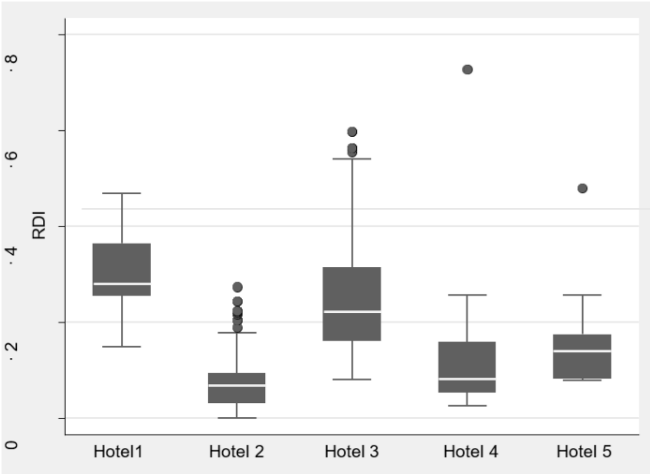

Figure 1. Box Plot of RDI among 5 hotels
Source: Own creation

Descriptive statistics of the RDI further indicate substantial variation across hotels. As illustrated in Figure 1, RDI differs significantly across properties (ANOVA $F(4,616) = 192.4$, $p < 0.001$), with hotel-level effects explaining a large proportion of variance ($\eta^2 = 0.55$). This variation suggests that pricing strategies, and their potential effects, are not uniform across hotels.

Table 2. Three domestic OTAs' penetration rates among sample hotels

Hotel	Channel 4	Channel 5	Channel 6	Total
1	3.30%	17.87%	78.82%	100%
2	12.85%	30.19%	56.97%	100%
3	6.24%	20.61%	73.15%	100 %
4	4.27%	13.47%	82.26%	100%
5	3.03%	4.26%	92.71%	100%
Total	**7.07%**	**21.29%**	**71.64%**	**100%**

Source: Own creation

To focus on meaningful competitive dynamics, subsequent analyses concentrate on the three primary domestic channels, whose penetration rates are summarized in Table 2. Within this reduced set, the dominant channel accounts for approximately 72% of bookings, followed by the mid-level channel (21%) and the least channel (7%). These differences form the basis for analyzing how rate disparity relates to demand allocation across channels with varying levels of market power.

4.2 Rate disparity and demand allocation: pairwise channel analysis

First, the differences in relative prices were examined across channels to predict the allocation of bookings between channel pairs. Initial analyses based on linear specifications yield limited and inconsistent results. Because channel pairs differ substantially in their combined daily market shares, we also grouped observations into low, regular, and high share conditions to examine whether competitive intensity alters the price–demand relationship.

Across different market share conditions (low, regular, high), the price ratio between channels is not a reliable predictor of room-night ratios. For example, when comparing the least and mid-level channels, the price ratio is only weakly significant in the regular-share condition ($p < 0.066$, $R^2 = 0.01$) and exhibits a reversed relationship in low-share conditions ($p < 0.048$, $R^2 = 0.04$). Similarly, when comparing the least and most dominant channels, price ratio is only significant in the regular-share condition ($p < 0.014$, $R^2 = 0.02$). These low R^2 values indicate that price explains only a very small fraction of variation in demand allocation. The lack of consistent predictive power across share conditions suggests that market-share differences do not fundamentally alter the weak association between price and room-night allocation.

Table 3. Curve estimation – the room night ratio between every two channels

Least channel vs. Mid channel

Predictor	**Coef.**	**SE *B***	***t***	***P***
Price Ratio channel 4 to 5	-2.904	0.720	-4.030	0.001
Price Ratio channel 4 to 5 - Quadratic	0.787	0.180	4.370	0.001
Constant	2.567	0.552	4.650	0.001

Note: R^2=0.035 (N = 539, p <0.001), f^2 =0.036 Cohen's (1988) effect size statistic for regression analyses.

Least channel vs. Most channel

Predictor	**Coef.**	**SE *B***	***t***	***P***
Price Ratio channel 4 to 6	-0.684	0.174	-3.920	0.001
Price Ratio channel 4 to 6 - Quadratic	0.146	0.046	3.160	0.002
Constant	0.671	0.134	5.000	0.001

Note: R^2=0.03 (N = 621, p <0.001), f^2 =0.031 Cohen's (1988) effect size statistic for regression analyses.

Mid channel vs. Most channel

Predictor	**Coef.**	**SE *B***	***t***	***P***
Price Ratio channel 5 to 6	226.804	44.067	5.150	0.001
Price Ratio channel 5 to 6 - Quadratic	-215.220	41.704	-5.160	0.001
Price Ratio channel 5 to 6 - Cubic	67.325	13.083	5.150	0.001
Constant	-78.540	15.439	-5.090	0.001

Note: R^2=0.095 (N = 621, p <0.001), f^2 =0.104 Cohen's (1988) effect size statistic for regression analyses.

Source: Own creation

Given these patterns, the analysis was extended to allow for non-linear relationships. As shown in Table 3, polynomial specifications indicate statistically significant but modest relationships between price ratio and room-night ratios. For example, the relationship between the least and mid-level channels follows a quadratic form ($R^2 = 0.035$; Cohen's $f^2 = 0.036$), and the least–most comparison shows a similarly modest quadratic relationship ($R^2 = 0.03$), while the relationship between the mid-level and dominant channels follows a cubic form ($R^2 = 0.095$; Cohen's $f^2 = 0.104$).

Although these models improve statistical fit, their explanatory power remains limited. Even in the strongest case, less than 10% of the variation in demand allocation is explained by price differences. These findings suggest that rate disparity has a statistically detectable but economically weak and non-linear effect on demand allocation.

4.3 The moderating role of hotel characteristics

To assess whether these relationships vary with hotel-level characteristics, hotel-specific control variables were utilized in hierarchical regression models. The results, presented in Table 4, show a substantial increase in explanatory power when hotel indicators are included.

For example, the inclusion of hotel variables significantly increases R^2 across all specifications, with Model 2 values spread rising from 0.03 - 0.09 to the wider 0.09 - 0.37 one, indicating that hotel characteristics explain a much larger portion of variation in demand allocation than price differences. At the same time, the statistical significance of price variables is reduced or eliminated in several models. In particular, the price ratio and its polynomial terms lose significance in both the least–most and mid–most comparisons once hotel effects are controlled for, while only the least–mid comparison retains a statistically significant, but reduced, relationship.

Table 4. Hierarchical regression - the room night ratio between every two channels

Least channel vs. Mid channel						
	Model 1			**Model 2**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 4 to 5	-2.904	0.720	0.001	-2.211	0.729	0.003
Price Ratio channel 4 to 5 - Quadratic	0.787	0.180	0.001	0.627	0.180	0.001
Hotel 2				0.300	0.058	0.001
Hotel 3				0.082	0.080	0.305
Hotel 4				0.212	0.067	0.002
Hotel 5				-0.214	0.146	0.143
R^2	0.035			0.096		
ΔR^2	0.032			0.086		
R^2 change				0.061		
N=539						

Least channel vs. Most channel						
	Model 1			**Model 2**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 4 to 6	-0.684	0.174	0.001	0.259	0.192	0.179
Price Ratio channel 4 to 6 - Quadratic	0.146	0.046	0.002	-0.055	0.047	0.246
Hotel 2				0.244	0.017	0.001
Hotel 3				0.044	0.025	0.088
Hotel 4				0.009	0.021	0.654
Hotel 5				-0.013	0.025	0.606
R^2	0.029			0.315		
ΔR^2	0.026			0.308		
R^2 change				0.286		
N=621						

Mid channel vs. Most channel						
	Model 1			**Model 2**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 5 to 6	226.804	44.067	0.001	5.557	44.966	0.902
Price Ratio channel 5 to 6 - Quadratic	-215.220	41.704	0.001	-6.304	42.637	0.883
Price Ratio channel 5 to 6 - Cubic	67.325	13.083	0.001	2.191	13.383	0.870
Hotel 2				0.343	0.028	0.001
Hotel 3				0.148	0.043	0.001
Hotel 4				-0.063	0.032	0.048
Hotel 5				-0.115	0.039	0.003
R^2	0.095			0.375		
ΔR^2	0.090			0.368		
R^2 change				0.281		
N=621						

Source: Own creation

This pattern suggests that the effect of rate disparity is strongly moderated by hotel-specific attributes, such as brand positioning, location, and perceived quality. In other words, the same price difference may produce different outcomes depending on the hotel context. The dominance of hotel-level predictors in the hierarchical models underscores that structural product characteristics, rather than daily price movements, are the primary drivers of how demand is allocated across channels. These findings highlight that price operates within a broader system in which product characteristics play a dominant role.

4.4 Market share analysis: price, parity and platform power

Next, the analysis examines how rate disparity and rate parity are associated with market share between competing channels. Results from hierarchical regression models are presented in Table 5.

Table 5. Hierarchical regressions to compare market shares between two channels

Market Share - Least Channel vs. Mid-Channel

	Model 1			**Model 2**			**Model 3**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 4 to 5	0.096	0.083	0.252	0.088	0.084	0.293	0.126	0.083	0.129
Price Consistency between channel 4 & 5				-0.017	0.020	0.403	0.010	0.021	0.614
Hotel 2							0.164	0.026	0.001
Hotel 3							0.016	0.036	0.651
Hotel 4							0.120	0.031	0.001
Hotel 5							0.081	0.033	0.014
R^2	0.002			0.003			0.073		
ΔR^2	0.001			<0.001			0.064		
R^2 change				0.001			0.070		
N=621									

Market Share - Least Channel vs. Most Channel

	Model 1			**Model 2**			**Model 3**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 4 to 6	-0.119	0.031	0.001	-0.093	0.030	0.002	0.014	0.027	0.611
Price Consistency between channel 4 & 6				0.076	0.011	0.001	0.027	0.009	0.003
Hotel 2							0.158	0.008	0.001
Hotel 3							0.043	0.012	0.001
Hotel 4							0.021	0.010	0.040
Hotel 5							0.004	0.011	0.738
R^2	0.023			0.094			0.453		
ΔR^2	0.021			0.091			0.448		
R^2 change				0.071			0.359		
N=621									

Market Share - Mid-Channel vs. Most Channel

	Model 1			**Model 2**			**Model 3**		
Predictor	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***	**Coef.**	**SE *B***	***P***
Price Ratio channel 5 to 6	-0.579	0.081	0.001	-0.478	0.077	0.001	-0.183	0.075	0.014
Price Consistency between channel 5 & 6				0.110	0.013	0.001	0.005	0.012	0.660
Hotel 2							0.160	0.013	0.001
Hotel 3							0.073	0.017	0.001
Hotel 4							-0.046	0.014	0.001
Hotel 5							-0.108	0.016	0.001

R^2	0.077	0.176	0.471
ΔR^2	0.075	0.174	0.466
R^2 change		0.099	0.295
N=621			

Source: Own creation

For the least–mid pair, neither price ratio ($p = 0.403$) nor price consistency ($p = 0.182$) significantly predicts market share, while hotel characteristics account for most of the explained variance. Hotels 2, 4, and 5 show significant effects ($p < 0.001$), indicating that hotel attributes drive consumers' allocation between these two lower-power channels more than price differences.

For the pair of least and most dominant channels, the price ratio initially appears to significantly predict market share ($\Delta R^2 = 2.1\%$, $p < 0.001$). However, when rate consistency and hotel characteristics are added, the effect of price becomes insignificant ($p > 0.60$), while hotel variables account for a substantial portion of the variance (total $R^2 = 45.3\%$).

A similar pattern is observed for the mid-level and dominant channels. While both price ratio and parity status are significant predictors in simpler models, their effects disappear after controlling for hotel characteristics, which account for up to 46.6% of the variance.

These results provide strong support for the hypothesis that the impact of rate disparity and parity on demand allocation is contingent on both platform power and hotel characteristics. In particular, the dominant channel maintains a strong market position regardless of relative price, suggesting that platform dominance constrains the effectiveness of price-based competition.

4.5 Seasonality and demand conditions

In the next phase, the analysis examines how rate disparity and demand allocation vary across demand conditions. Results from ANOVA and regression analyses are presented in Table 6 and Figure 2.

Table 6. Linear regression – Demand impacts Rate Disparity Index (RDI)

Predictor	**Coef.**	**SE *B***	***t***	***P***
Low Demand	-0.020	0.007	-2.930	0.004
Normal Demand	-0.025	0.006	-4.240	0.001
Constant	0.101	0.005	20.780	0.001

Note: R^2=0.032 (N = 557, p <0.001)
Source: Own creation

Rate disparity levels differ significantly across demand seasons ($F_{(2,554)} = 9.10$, $p < 0.001$), with higher disparity observed during high-demand periods. However, the effect size is relatively small ($\eta^2 = 0.032$), indicating that seasonality explains only a modest portion of variation in pricing behavior. Additional analyses at the hotel level suggest stronger seasonal effects. For four of the five hotels (all except hotel 3), RDI varies significantly across demand seasons (ps < 0.05), with medium effect sizes ($\eta^2 > 0.063$). These results indicate that while seasonality affects RDI overall, the magnitude of this effect differs substantially across hotels.

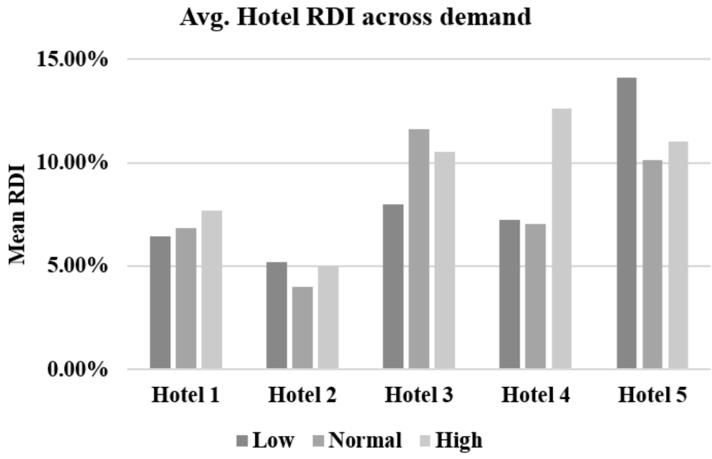

Figure 2. Bar chart of RDI among 5 hotels by demand seasons
Source: Own creation

Further analyses show that the impact of rate disparity on channel market penetration varies across demand conditions. As shown in Table 7, both demand season and rate disparity significantly predict channel penetration, but their effects differ by channel. For example, the dominant channel experiences reduced penetration during both low- and high-demand periods, while mid-level channels gain share under these conditions.

For the lowest volume channel (Channel 4), market penetration is 1.6 percentage points higher in low-demand seasons than in normal seasons ($p < 0.03$), and RDI does not significantly affect its penetration ($p = 0.21$).

For the mid-level channel (Channel 5), penetration increases by 3.9% in low-demand seasons and 4.7% in high-demand seasons relative to normal periods (ps < 0.01). RDI negatively affects its share: a 1% increase in RDI reduces penetration by 0.42 percentage points ($p < 0.001$).

For the dominant channel (Ctrip, Channel 6), the pattern reverses: penetration decreases by 5.5% in low-demand seasons and 4.4% in high-demand seasons (ps < 0.01). RDI positively affects its share: a 1% increase in RDI increases penetration by 0.5 percentage points ($p < 0.001$).

Table 7. Multivariate Multiple Regression – Channel Market Penetration

Least Channel Market Penetration

Predictor	**Coef.**	**SE *B***	***T* value**	***P***
Low Demand	0.016	0.007	2.19	0.029
High Demand	-0.004	0.008	-0.51	0.612
RDI	-0.071	0.056	-1.27	0.205
Constant	0.065	0.006	10.76	0.001
R^2 = 0.015, RMSE=0.073, MODEL P<0.037				

Mid-Channel Market Penetration

Predictor	**Coef.**	**SE *B***	***T* value**	***P***
Low Demand	0.039	0.013	2.91	0.004
High Demand	0.047	0.014	3.41	0.001
RDI	-0.423	0.099	-4.27	<0.001
Constant	0.187	0.011	17.38	<0.001
R^2 = 0.05, RMSE=0.130, MODEL P<0.001				

Most Channel Market Penetration

Predictor	Coef.	SE *B*	*T* value	*P*
Low Demand	-0.055	0.017	-3.29	0.001
High Demand	-0.044	0.017	-2.54	0.011
RDI	0.496	0.124	4.00	<0.001
Constant	0.748	0.014	55.36	<0.001
R^2 = 0.046, RMSE=0.163, MODEL P<0.001				

Note: N=557
Source: Own creation

When incorporating the availability of the lowest price (Table 8), the explanatory power of the models increases substantially. Channels offering the lowest price capture significantly higher market shares, but these gains are primarily redistributed from other channels rather than reflecting new demand. This interpretation is supported by two aspects of the results. First, because market penetration is measured as a share of total OTA room nights, the dependent variable reflects relative allocation rather than absolute booking volume. Second, the regression results show structured and partial redistribution patterns: when the dominant channel loses market share, the least and mid-level channels absorb different proportions of that loss depending on demand conditions and which channel offers the lowest price.

For the least channel, its market penetration increases by 1.4 percentage points during low-demand seasons, representing roughly 30% of Ctrip's 4.7-point decline in the same period. When the least channel offers the lowest price, its penetration rises by 5.2 percentage points, absorbing 29.5% of Ctrip's 17.6-point loss under this price condition. Given that the least channel's baseline penetration is only 7%, a 5.2-point increase constitutes a substantial relative shift.

For the mid-level channel, the absorption is even larger. Its penetration increases by 4 percentage points during high-demand seasons, fully offsetting Ctrip's seasonal decline. When the mid-channel holds the lowest price, its penetration increases by 8.9 percentage points, absorbing 75.4% of Ctrip's 11.8-point loss. Even when the least channel offers the lowest price, the mid-channel still gains 12.3 percentage points, accounting for 69.9% of Ctrip's 17.6-point loss.

These patterned, partial absorption effects suggest that the observed changes in market penetration are largely driven by the redistribution of existing demand across channels, rather than by increases in total room nights.

Table 8. Improved Multivariate Multiple Regression – Channel Market Penetrations based on demand, RDI and cheapest price availability

Least Channel Market Penetration

Predictor	Coef.	SE *B*	*T* value	*P*
Low Demand	0.014	0.007	1.89	0.060
High Demand	-0.007	0.007	-0.90	0.370
RDI	-0.002	0.054	-0.03	0.974
Cheapest on channel 4	0.052	0.008	6.92	<0.001
Cheapest on channel 5	0.029	0.007	4.15	<0.001
Constant	0.041	0.007	6.02	<0.001
R^2 = 0.10, RMSE=0.070, MODEL P<0.001				

Mid-Channel Market Penetration

Predictor	Coef.	SE *B*	*T* value	*P*
Low Demand	0.033	0.012	2.74	0.006
High Demand	0.040	0.013	3.15	0.002
RDI	-0.245	0.092	-2.67	0.008
Cheapest on channel 4	0.123	0.013	9.58	<0.001
Cheapest on channel 5	0.089	0.012	7.44	<0.001
Constant	0.124	0.012	10.69	<0.001
R^2 = 0.212, RMSE=0.118, MODEL *P*<0.001				

Most Channel Market Penetration

Predictor	Coef.	SE *B*	*T* value	*P*
Low Demand	-0.047	0.015	-3.14	0.002
High Demand	-0.034	0.016	-2.20	0.028
RDI	0.250	0.112	2.23	0.026
Cheapest on channel 4	-0.176	0.016	-11.17	<0.001
Cheapest on channel 5	-0.118	0.015	-8.07	<0.001
Constant	0.835	0.014	58.94	<0.001
R^2 = 0.247, RMSE=0.145, MODEL *P*<0.001				

Note: N=557
Source: Own creation

However, when hotel characteristics are included (Table 9), the significance of many pricing-related variables decreases, highlighting the important role of hotel-specific factors in demand allocation. In this specification, RDI becomes completely non-significant (p = 0.914), the lowest price in the least channel loses significance (p = 0.088), and only the lowest price in the mid-channel remains a significant predictor (p = 0.017), indicating that pricing effects are considerably reduced after accounting for systematic hotel-level heterogeneity.

Table 9. Final Multiple Regression – Channel Market Penetration based on demand season, RDI, cheapest price availability, and hotel specification

Most Channel Market Penetration

Predictor	Coef.	SE *B*	*T* value	*P*
Low Demand	-0.045	0.011	-4.05	<0.001
High Demand	-0.034	0.012	-2.94	0.003
RDI	-0.009	0.087	-0.11	0.914
Cheapest on channel 4	-0.026	0.015	-1.71	0.088
Cheapest on channel 5	-0.033	0.014	-2.40	0.017
Hotel 2	-0.239	0.014	-17.57	<0.001
Hotel 3	-0.100	0.018	-5.67	<0.001
Hotel 4	0.020	0.014	1.41	0.160
Hotel 5	0.092	0.017	5.36	<0.001
Constant	0.851	0.014	61.73	<0.001
R^2 = 0.587, RMSE=0.108, MODEL *P*<0.001				

Note: N=557
Source: Own creation

4.6 Demand redistribution rather than demand generation

Across all model specifications, there is no evidence that rate disparity leads to an increase in total demand. Instead, the results consistently show that price differences are associated with shifts in demand across channels.

For example, when a channel offers the lowest price, it captures a larger share of bookings, but these gains correspond to losses in other channels' market share (Tables 7-8). This pattern indicates that rate disparity primarily functions as a redistribution mechanism within a fixed demand environment, rather than as a tool for increasing overall demand.

4.7 Summary of findings

Taken together, the results indicate several consistent patterns. Price differences among channels have limited explanatory power, as shown by low R^2 values across models. The relationship between price and demand allocation is non-linear. Hotel characteristics explain a substantially larger portion of variation than price. Platform dominance constrains the effectiveness of price-based competition. Finally rate disparity redistributes demand across channels rather than increasing total demand These findings suggest that rate disparity operates as a weak and context-dependent mechanism, whose effectiveness is shaped by platform power, hotel attributes, and demand conditions rather than price differences alone.

5. Conclusions and discussions

5.1 Interpreting the role of rate disparity in multi-channel environments

The results provide a consistent picture: while rate disparity is statistically associated with changes in demand allocation, its effects are limited in magnitude, non-linear, and highly context dependent. Across model specifications (Tables 3-5), price differences explain only a small proportion of variation in booking distribution, with low R^2 values and modest effect sizes. Even when significant, the economic impact of these effects appears limited.

This finding challenges the conventional assumption (rooted in standard economic theory) that lower prices should systematically attract demand. In the context of multi-channel hotel distribution, price differences do not operate as a strong or reliable lever for influencing booking behavior. Instead, they function as a secondary mechanism, whose effects are constrained by broader structural factors.

In particular, the results show that platform power and hotel characteristics dominate price effects. The introduction of hotel-level controls (Table 4) substantially increases explanatory power while reducing or eliminating the significance of price variables. Similarly, the dominant channel retains a large share of demand regardless of relative price (Tables 1 and 5), indicating that consumer choice is strongly anchored to platform preference.

Taken together, these findings suggest that rate disparity operates within a platform-mediated system, where consumer behavior is shaped not only by price but also by visibility, trust, habitual usage, and perceived reliability of distribution channels.

5.2 Price as a context-dependent and non-linear mechanism

The non-linear relationships identified in Table 3 further complicate the role of rate disparity. The effect of price differences on demand allocation does not follow a simple linear pattern. Small price differences often have negligible effects, while larger disparities produce only modest and sometimes inconsistent shifts in demand.

This suggests the presence of threshold effects and diminishing returns. Consumers may ignore minor price differences due to search costs, loyalty, or perceived risk, while larger differences may trigger switching behavior only under specific conditions. Even then, the ability of lower-priced channels to capture demand is constrained by their relative market position.

Moreover, the instability of results across different channel pairs and market conditions indicates that price effects are highly sensitive to context. The same level of rate disparity may produce different outcomes depending on channel power, hotel characteristics, and baseline market share.

These findings reinforce the view that pricing strategies cannot be evaluated in isolation but must be understood as part of a broader system of interacting factors.

5.3 Demand redistribution versus demand generation

A central insight from the results is that rate disparity primarily drives redistribution of demand across channels rather than generation of new demand. Across all specifications (Tables 7-8), gains in market share for one channel correspond to losses for others, with no evidence of an increase in total bookings.

This distinction is particularly important in capacity-constrained environments such as hotels, where short-term demand is relatively fixed. In such settings, pricing decisions regarding parity may be associated with where bookings occur rather than whether they occur.

This insight helps reconcile the limited effectiveness of rate disparity observed in the data. Even when price differences succeed in shifting bookings, they do so within a zero-sum framework. As a result, the strategic value of rate disparity depends not only on its ability to attract bookings but also on which channels gain or lose demand.

5.4 Implications for channel economics and profitability

While this study does not directly measure profitability, the results have important implications for the economic outcomes of pricing strategies. Because distribution channels differ in their cost structures, particularly in terms of commissions, changes in demand allocation across channels can materially affect profitability.

For example, shifting bookings toward a lower-priced channel may not improve financial performance if that channel is associated with higher distribution costs. Conversely, directing demand toward more cost-efficient channels may enhance profitability even in the absence of price advantages.

The findings suggest that rate disparity should be evaluated not only in terms of demand outcomes but also in terms of its impact on channel mix, which is a key determinant of profitability. In this sense, the limited ability of rate disparity to influence demand allocation may reduce its effectiveness as a profitability-enhancing strategy.

5.5 Theoretical implications

This study contributes to the literature by offering a more nuanced understanding of pricing in platform-based distribution systems. Firstly, the findings challenge the traditional application of the law of demand in multi-channel environments. While lower prices are expected to attract demand, the results show that this relationship is weak and contingent on contextual factors. This suggests that price alone is insufficient to explain demand allocation in platform-mediated markets.

Secondly, the study highlights the importance of platform power as a moderating force. The dominance of leading OTAs constrains the effectiveness of price-based competition, indicating that demand allocation is shaped by structural features of the distribution system rather than by price differences alone.

Thirdly, by distinguishing between demand generation and demand redistribution, the study clarifies an important conceptual issue that has received limited attention in prior research. This distinction is critical for understanding the true impact of pricing strategies in capacity-constrained industries. Finally, the results point to the need for a more integrated theoretical framework that combines pricing, platform competition, and product characteristics. Rather than treating these elements independently, future research should examine how they interact to shape demand outcomes.

5.6 Managerial implications

The findings have several important implications for practitioners. Firstly, the results suggest that rate disparity is a relatively weak tool for influencing demand allocation. While price differences can produce some shifts in bookings, their effects are limited and highly dependent on context. Managers should therefore be cautious in relying on price-based strategies as a primary means of driving channel performance.

Secondly, the dominance of leading platforms indicates that competing solely on price is unlikely to overcome platform advantages. Hotels should consider alternative strategies, such as improving visibility, strengthening partnerships, and enhancing customer engagement, to influence booking behavior.

Thirdly, the redistribution of demand across channels has direct implications for profitability. Because channels differ in their cost structures, changes in channel mix can affect margins even when total demand remains unchanged. Managers should therefore evaluate pricing decisions in conjunction with channel costs and consider the economic value of bookings across channels, not just their volume.

Finally, the results suggest that pricing strategies should be adapted to demand conditions. Rate disparity may have greater impact in low-demand periods or among secondary channels, but its effectiveness remains limited in the presence of strong platform dominance.

5.7 Limitations and future research

This study has several limitations that should be acknowledged. Firstly, the analysis is based on a limited number of hotels. While the dataset provides rich, high-frequency observations over time, the findings should be interpreted as analytical insights into underlying mechanisms rather than statistically generalizable estimates. Future research could extend this analysis to a larger and more diverse sample of hotels and markets.

Secondly, the study focuses on demand allocation and does not directly measure profitability outcomes. Although the results highlight the potential economic implications of channel mix, future research could incorporate cost and margin data to examine how rate disparity affects profitability more directly.

Thirdly, the analysis does not account for certain platform-specific factors, such as ranking algorithms, promotional placements, and loyalty programs, which may influence booking behavior independently of price. Future research could explore how these factors interact with pricing strategies to shape demand allocation.

In addition, the dynamic nature of hospitality pricing introduces a potential two-way relationship between price and demand. Observed price disparity may partly reflect underlying demand conditions rather than shape them, which may affect how the estimated coefficients should be interpreted. Finally, while the study identifies non-linear and context-dependent effects of rate disparity, further work is needed to better understand the underlying behavioral mechanisms driving these patterns, including consumer search behavior, trust, and channel loyalty.

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