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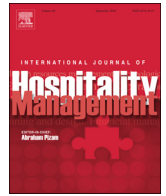
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## Research Paper

## Financial consequences of competitive set choice

James Hesford<sup>a</sup>, Kelly Hoffmann<sup>b</sup>, Nicolas Mangin<sup>c</sup>, Michael J. Turner<sup>d,\*</sup><sup>a</sup> University of Lethbridge, Room S6037, 345 6 Ave SE, Calgary AB T2G 4V1, Canada<sup>b</sup> Hannover, Germany<sup>c</sup> University of Groningen, P.O. Box 800, 9700 AH Groningen, the Netherlands<sup>d</sup> The University of Queensland, UQ Business School, Brisbane, QLD 4072, Australia

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## ABSTRACT

This study examines the financial consequences of competitive set choice using a sample of 312 hotels in a major metropolitan area in the United States. We document existence of asymmetric competitor monitoring, finding just 55% of monitoring is reciprocal; that is, about half of managers “agree,” by virtue of monitoring one another, on being direct competitors. Monitoring reciprocity is positively associated with performance through average daily rates. With total revenue unchanged, profits are higher through lower occupancy and lower total costs. We examine alternative competitive sets formed using strategic groups- and customer-based approaches, comparing these to actual compsets. We found that performance declines when managers deviate from these alternative sets. Post-hoc analyses provide insight on how overlapping compsets impact rates, occupancy and revenue. Our study is of value to academics and practitioners, providing evidence on the financial impact of competitive monitoring, and insights for managers who choose competitive sets.

## 1. Introduction

The objective of this study is to investigate the financial performance consequences of accuracy in manager-generated competitive sets (compsets). Resource-based theory suggests that firms derive strategic competitive advantage by gathering information on their competitors (Day and Wensley, 1988; Hunt and Morgan, 1995). This information, also referred to as competitive intelligence, enables managers to develop superior strategies and make better resource allocation decisions that lead to improved performance (Baines and Langfield-Smith, 2003; Christensen and Feltham, 2003; Ward, 1992). This implies that the performance consequences of competitor monitoring are contingent on a necessary precondition: Accuracy, in terms of which competitors managers choose to be part of their compset. If intelligence gathered by managers is inaccurate, it will not be useful, and may be harmful (Calof and Skinner, 1998).

Focusing on the hotel industry, we follow Gur and Greckhamer's (2019) three views on how compsets may be generated: strategic groups-based, customer-based and manager-generated. Our study is motivated by prior studies documenting hotel managers' disagreement on which criteria are most important in defining competitors (Baum and Lant, 2003; Kim and Canina, 2011; Köseoglu et al., 2016; Li and Netessine, 2012; Mohammed et al., 2014). Manager-generated compsets may include differing degrees of customer- and strategic groups-

based data.

Managers rely on competitor information to make strategic decisions regarding pricing, as a firm's positioning in the market is a combination of its customer segment and price point (Dube et al., 1999). Their pricing strategies impact competitiveness in terms of revenue and demand, and managers use pricing as a tool to improve performance (Kim et al., 2014). With high operating leverage, profits are sensitive to fluctuations in demand (Singal, 2015). Along with sensitivity to environmental and economic uncertainty, managers have difficulty matching supply with short-term demand (Hsu and Jang, 2008; Mia and Patiar, 2001; Singal, 2012). Pricing is key to dealing with short-term demand, and understanding competitors' pricing through monitoring is critical to improving pricing strategy (Heo and Hyun, 2015).

We are unaware of research examining the link between different types of compset formation and hotel performance. With a monitoring database from a third-party benchmarking firm, we fill this gap. Our data includes information on hotel monitoring behavior and sales performance. Our results indicate that greater accuracy in competitor identification positively impacts hotel performance. Managers can increase monitoring accuracy by using strategic groups-based approaches, identifying competitors based on similarity in size, price and location, or by ascertaining competitors in customers' consideration sets.

\* Corresponding author.

E-mail addresses: [james.hesford@uleth.ca](mailto:james.hesford@uleth.ca) (J. Hesford), [n.j.b.mangin@rug.nl](mailto:n.j.b.mangin@rug.nl) (N. Mangin), [m.turner@business.uq.edu.au](mailto:m.turner@business.uq.edu.au) (M.J. Turner).

The next two sections review the literature and develop hypotheses. This is followed by sections for our research method and results. After discussing our results, we conclude with limitations and suggestions for future research.

## 2. Literature review

### 2.1. Competitor monitoring and financial performance

According to resource-based theory, firms have numerous resources, and those which are unique are integral to gaining competitive advantage (Barney, 1991; Prahalad and Hamel, 2006; Wernerfelt, 1984). A key resource area is the knowledge-based view, wherein a firm's knowledge base is viewed as the greatest source of differentiation, enabling competitive advantage and higher performance (Dierickx and Cool, 1989; Grant, 1996; Lippman and Rumelt, 1982). Information gathered from competitor monitoring contributes to knowledge and is linked with strategy (Calof and Wright, 2008). An assumption of the knowledge-based view is that firms investing greater resources into knowledge creation reap greater benefits (Reus et al., 2009). Benefits stem from developing an understanding of their competitors, identifying areas of vulnerability of competitors and in assessing how competitors might react to one's own actions (Calof and Wright, 2008; Fuld, 1991; Pepper, 1999; Prescott and Smith, 1989; Tao and Prescott, 2000; Trim and Lee, 2008).

### 2.2. Conceptualizations of competitor identification

Competitor identification within an industry can be conceptualized in terms of strategic groups, customer preferences or the role of managerial cognition (Gur and Greckhamer, 2019). The strategic groups-based view of competition relies on managers choosing firms with similar characteristics and strategy to identify competitors. This means that not all firms in an industry may compete with each other (DeSarbo et al., 2006). This view implies that firms with similar characteristics are more likely to pose a competitive threat to each other (Kim and Canina, 2011). Characteristics commonly include firm size, location and pricing (Baum and Lant, 2003).

The customer-based view relies on customers' perceptions to identify which firms compete with each other (DeSarbo et al., 2006). Since customers are ultimately the ones who decide the outcome of the buying process, their consideration sets (i.e., the set of options considered during the buying process) contain firms with similar service offerings and are, therefore, competitive groups (Bergen and Peteraf, 2002). By definition, if a customer considers two firms to be potential substitutes, they are competing (DeSarbo et al., 2006).

The manager-generated view stresses the importance of managers' perceptions of other firms to identify competitors (Gur and Greckhamer, 2019). Information gathered by managers typically comes from a variety of formal and informal sources, which may include strategic groups-based and/or customer-based characteristics (Bergen and Peteraf, 2002; Eisenberg, 1984; Issack, 1978; Peteraf and Bergen, 2003; Simon, 1987).

### 2.3. Managerial cognition and compset choice

A key assumption of resource-based theory is bounded rationality, which implies that although individuals intend to be rational, they are only limitedly so (Simon, 1957). No scope for sustainable competitive advantage would exist if managers made perfectly rational decisions (Coff, 2003). Managers apply cognition to identify competitors based on their perception of other firms within their competitive environment, meaning their decisions are subject to cognitive limitations (Bergen and Peteraf, 2002; Gabaix et al., 2006; Panagiotou, 2007; Peteraf and Bergen, 2003; Reger and Huff, 1993). When applying cognition, managers tend to make non-optimal decisions with

unintentional (e.g., honest mistakes, imperfect techniques and inadequate data) and/or intentional biases (e.g., deliberate manipulation) (Flyvbjerg et al., 2003).

From a resource-based perspective, cognitive limitations emerge as overestimating attributes of the current compset (endowment effect), overlooking alternative compsets due to familiarity with the current compset (familiarity effect), and/or being averse to compset compositions that are extremely different to their current compset (extremeness aversion) (Heath and Tversky, 1991; Simonson and Tversky, 1992; Thaler, 1980). Managerial cognition results in adverse consequences to firm performance (Berger and Ofek, 1995; Scharfstein and Stein, 2000).

### 2.4. Hotel competitor identification practices

Baum and Lant (2003) examined how managers generate compsets in the hotel industry. Restricting managers' competitor identification criteria to strategic groups-based attributes of size, location and price, they document biases and misperceptions in weights managers attached to these attributes, ultimately finding that greater weight was placed on location at the expense of price. According to resource-based theory, a naïve manager is predisposed to apply equality heuristics (i.e., equal weights would be assigned to attributes) (Epley and Gilovich, 2001; Messick, 1993; Tversky and Kahneman, 1974). Developing expertise diminishes these effects, but high employee turnover – a characteristic of the hotel industry – inhibits development of expertise (Bardolet et al., 2011; Fox and Clemen, 2005; Tracey and Hinkin, 2008) and, therefore, optimal weights. Subsequent studies documented divergence between manager-generated, strategic groups-based and customer-based compsets.

Kim and Canina (2011) found differences across two distinct strategic groups-based compsets, one formed by clustering on average daily rate, and the other by product type classifications. Further, they document that managers and industry experts did not agree among themselves on the characteristics or methods for choosing compsets.

Li and Netessine (2012) compared a customer-based view of competition, analyzing online travel agency search and transaction data. Finding a 50 percent mismatch between strategic groups- and customer-based compsets, they concluded that hotels in a competitive market see themselves from their customers' perspective to capture business. Since customer-based information is realistic, firms should not rely solely on strategic groups-based sets.

Mohammed et al. (2014) found that managers consider only a limited number of factors or competitor characteristics when identifying direct competitors. These criteria commonly include strategic groups-based ones such as location, price, product offering and size, but managers may also incorporate customer-based factors, such as brand image or service delivery. Interestingly, they found that manager-generated and customer-based compsets displayed a similarity of only 60 percent.

Finally, Köseoglu et al. (2016) explored competitive intelligence practices in hotels. Interviewees did not demonstrate a high level of knowledge and awareness of competitive intelligence. Further, Köseoglu et al. (2020) ascertained that departments in a full-service Hong Kong hotel did not use formal competitive intelligence practices to guide daily operations.

## 3. Hypothesis development

Research has found that competitive market structures are asymmetric (Baum and Lant, 2003; Clark and Montgomery, 1999; DeSarbo et al., 2006). This means that firm A sees itself as competing with firm B, but firm B does not see itself as competing with firm A. Most firms do not agree whether they are competing directly, indirectly, or not at all (DeSarbo et al., 2006). Reciprocal relationships are those where two firms see each other as competitors, whereas non-reciprocal relationships are those where only one of two firms believe it is competing with

the other. A high degree of reciprocity among firm competitors (i.e., a high proportion of reciprocal ties) reflects a consensus that the firm is targeting the same customers. Low reciprocity infers a higher likelihood that a manager made mistakes when choosing the compset as there is disagreement between competitors. Therefore, monitoring reciprocity is a proxy for compset accuracy.

Consistent with resource-based theory is the idea that the knowledge a firm gathers from monitoring its competitors facilitates competitive advantage (Barney, 1991; Dierickx and Cool, 1989; Lippman and Rumelt, 1982; Prahalad and Hamel, 2006; Wernerfelt, 1984). Therefore, competitive set accuracy is linked to financial performance (Clark, 2011; Lee, 2015). Managers apply cognition but are subject to cognitive limitations that can adversely impact firm performance (Bergen and Peteraf, 2002; Berger and Ofek, 1995; Gabaix et al., 2006; Panagiotou, 2007; Peteraf and Bergen, 2003; Reger and Huff, 1993; Scharfstein and Stein, 2000). If competitor intelligence is inaccurate, then it is not useful, and may even be harmful (Calof and Skinner, 1998). Firms with a higher degree of reciprocal monitoring are expected to have more accurate competitor information and this knowledge should result in greater financial performance. Therefore, we posit:

**Hypothesis 1.** *Firms with a high degree of reciprocal monitoring have greater financial performance.*

The first view of compset formation is by scholars who assembled strategic groups-based compsets based on attributes such as size, price and location (Baum and Lant, 2003; Kim and Canina, 2011). The second view is customer-based since customers decide who is competing as they are choosing among competing firms (Li and Netessine, 2012). The third view is manager-generated (Mohammed et al., 2014). Li and Netessine (2012) found a 50 percent mismatch between strategic groups-based and customer-based compsets, while Mohammed et al. (2014) found manager-generated and customer-based compsets to display a similarity of only 60 percent. Given managers apply cognition with cognitive limitations, we posit that the three approaches lead to distinctly different compsets (Bergen and Peteraf, 2002; Gabaix et al., 2006; Panagiotou, 2007; Peteraf and Bergen, 2003; Reger and Huff, 1993). Formally, we hypothesize:

**Hypothesis 2.** *Manager-generated competitive sets deviate from both the strategic groups-based and from the customer-based view of competition.*

Researchers have used statistical methods to systematically search for and integrate available information to form strategic groups-based compsets (Baum and Lant, 2003; Kim and Canina, 2011). However, managers know their firm, its competitors, customers and local market, and their skill is key to a hotel’s success (Chung-Herrera et al., 2003; Kay and Russette, 2000). With managers having many responsibilities, time spent on competitor identification may be limited (Clark, 2011). Further, even when managers have time to apply cognition, their cognitive limitations may result in poor compset choices and, ultimately, lower performance (Bardolet et al., 2011; Fox and Clemen, 2005; Panagiotou, 2007; Reger and Huff, 1993). Accordingly, we hypothesize:

**Hypothesis 3.** *Managers’ deviation from strategic groups-based competitive sets results in lower financial performance.*

Managers try to find competitors that are targeting the same customer segments. These customer segments consider firms that they believe provide the best fit for their needs. However, when managers apply cognition with cognitive limitations, the identified competitors might not be the same as those of customers (Bergen and Peteraf, 2002; Gabaix et al., 2006; Panagiotou, 2007; Peteraf and Bergen, 2003; Reger and Huff, 1993). Customers are ultimately the ones who decide on competitors as they are the ones buying the products, meaning customer-based compsets are – by definition – the correct set (DeSarbo et al., 2006). In turn, higher agreement between manager-generated and customer-based compsets should lead to higher financial performance. Mismatches between criteria used by managers and customers to develop a compset indicate that managers fail to identify characteristics that customers care about. Therefore, we propose:

**Hypothesis 4.** *Managers’ deviation from customer-based competitive sets results in lower financial performance.*

## 4. Methods

### 4.1. Sample and procedures

Smith Travel Research (STR) provided us with anonymized monitoring and performance data from hotels in a major U.S. metropolitan area during the year 2012. The area is split into multiple distinct “tracts,” including the downtown core, airport and suburbs. These tracts – similar, but not identical to U.S. Census Bureau tracts – are shown in Table 1 along with the number of hotels. A number of prior studies used hotels in New York City. Hotels in the downtown core are quite different from airport and suburban hotels and, in choosing our sample market, we sought to include the entire area to enhance the generalizability of our findings. Further, we requested a market in which one of the authors had extensive knowledge, helping us verify the construction of the strategic groups- and customer-based competitive sets. Our data is from a third-party benchmarking firm, to which hotels voluntarily submit performance data. While anonymous, the data includes monitoring behavior, area location, hotel class, operation type, revenues, rooms available and sales volume. These data, along with anonymous identifying codes, allow us to assess performance and control for multiple variables that impact performance.

We excluded economy-lodging and midscale hotels.<sup>1</sup> Excluding these two hotel property types resulted in a sample of 337 hotels across the remaining four chain scales (Upper Midscale, Upscale, Upper scale and Luxury). Another 25 properties were excluded due to missing data. These omitted properties appeared to be randomly distributed across scales and locations and, therefore, will not impact our results. Properties included in the sample are mostly chain hotels.

**Table 1**  
Hotels by Tract.

Tract	Sample Size
Airport	30
Downtown	82
Tract 1	13
Tract 2	45
Tract 3	33
Tract 4	54
Tract 5	30
Tract 6	16
Tract 7	9

N = 312.

<sup>1</sup> First, these hotels tend to be smaller, independent properties with less-sophisticated managers. Second, a large proportion of these properties do not submit separate financial data, likely resulting in sample selection bias (average response rates are 51% vs. > 92% for the other hotel categories). In addition to this lower response rate, Li and Netessine (2012) found that one- and two-star hotels do not have meaningful correlations between competitors’ hotel prices, unlike hotels with higher star ratings. For this reason, Li and Netessine also excluded one- and two-star hotels. Low, nonsignificant price correlations between competing one- and two-star hotels imply these properties fail to adjust prices consistent with competitors’ prices. Therefore, reciprocal monitoring behavior would have no influence on average daily rates or revenue per available room in these hotel classes.

4.2. Impact of monitoring reciprocity on performance

To test hypothesis 1, we estimate the model below:

$$\begin{aligned}
 Performance_i = & \beta_0 + \beta_1 \text{ Reciprocal Monitoring} \\
 & + \beta_2 \text{ Market Concentration} + \beta_3 \text{ Quality} + \sum_{q=2}^4 \gamma_q \text{ Scale} \\
 & + \sum_{i=2}^9 \xi_i \text{ Tract} + \sum_{i=2}^3 \lambda_i \text{ Operation} + \epsilon_i
 \end{aligned} \tag{1}$$

where  $Performance_i$  is Average Daily Rate (ADR) and Revenue per Available Room (RevPAR) for hotel  $i$ . Model variables are described below.

4.3. Deviation of manager-generated competitive sets from alternative sets

Hypothesis 2 was tested by building three compsets. The first compset was built from actual hotel monitoring behavior. The competitors a hotel monitors form the *manager-generated* compset as managers decide on compset formation (Dev et al., 1995) subject to STR’s restrictions (to maintain confidentiality of suppliers’ individual data). The second compset, a strategic groups-based set, was constructed by computing the similarity of each hotel ( $i$ ) to all other metropolitan-area hotels ( $j$ ’s). Criteria used in the literature has been location, size and price. As mentioned above, resource-based theory suggests naïve managers apply equal weights to these criteria. Given high employee turnover in the hotel industry, equal weighting is a sound theoretical basis for the following scoring:

$$\text{Similarity score}_{i,j} = \frac{1}{3} \text{ Size similarity}_{i,j} + \frac{1}{3} \text{ Price similarity}_{i,j} + \frac{1}{3} \text{ Location similarity}_{i,j}$$

*Size (Price) similarity* is  $1/(1 + |z_i - z_j|)$  where  $|z_i - z_j|$  is the absolute value of the difference in standardized sizes (prices) between hotel  $i$  (focus hotel) and  $j$  (target, or monitored hotel). *Location similarity* is 1 if hotel  $i$  was in the same tract as  $j$ , otherwise it is 0. With a mean size of 224.2 rooms, mean ADR of \$122 and location similarity as a binary measure, using raw measures would be like combining apples, oranges and bananas. Standardized measures are unitless and its common scale eliminates the greater weight that would be given to size differences (due to smaller price deviations). With standardized values, these attributes can be meaningfully combined. After computing a matrix of similarity scores, the six most-similar competitors to the focus hotel were chosen as the compset. Set size was limited to six as this was the median and modal size of actual compsets. The third set, a *customer-based* one, was built using data from TripAdvisor, a company publishing hotel reviews and providing booking services. We used their web site’s “Customers Also Viewed” data, recording hotels that customers also viewed for each hotel in our sample. As with the strategic groups-based sets, we limited the customer-based sets to six competitors. For both sets we examined alternative set size as a robustness check on our results.

4.4. Performance impact of deviation from strategic groups-based sets

To test Hypothesis 3, we estimate the following model:

$$\begin{aligned}
 Performance_i = & \beta_0 + \beta_1 \text{ Compset Similarity, Strategic Groups-Manager} \\
 & + \beta_2 \text{ Market Concentration} + \beta_3 \text{ Quality} + \sum_{q=2}^4 \gamma_q \text{ Scale} \\
 & + \sum_{i=2}^9 \xi_i \text{ Tract} + \sum_{i=2}^3 \lambda_i \text{ Operation} + \epsilon_i
 \end{aligned} \tag{2}$$

4.5. Performance impact of deviation from customer-based sets

To test our final hypothesis, H4, we estimate the following model:

$$\begin{aligned}
 Performance_i = & \beta_0 + \beta_1 \text{ Compset Similarity, Customer-Manager} \\
 & + \beta_2 \text{ Market Concentration} + \beta_3 \text{ Quality} + \sum_{q=2}^4 \gamma_q \text{ Scale} \\
 & + \sum_{i=2}^9 \xi_i \text{ Tract} + \sum_{i=2}^3 \lambda_i \text{ Operation} + \epsilon_i
 \end{aligned} \tag{3}$$

4.6. Measures

4.6.1. Dependent variables

Financial performance was assessed using two common metrics: ADR and RevPAR. ADR is revenue for 2012 divided by the number of rooms rented and amounts to the average price. RevPAR, a key lodging industry metric, is revenue for 2012 divided by the number of rooms available. This measure is impacted by a firm’s average price (i.e., ADR) and its ability to utilize available capacity (i.e., its occupancy).

4.6.2. Independent variables

*Reciprocal monitoring percentage* was calculated based on the firm’s actual monitoring behavior. It is the number of reciprocal monitoring ties a property has, divided by its total number of monitoring ties. For example, assume *Acme* hotel in the airport tract monitors five hotels. If one or more of the five hotels follows *Acme*, we say there is reciprocity of monitoring. The proportion of the five hotels that reciprocate monitoring is our reciprocal monitoring percentage. If no (all) hotels reciprocate monitoring *Acme*, reciprocal monitoring percentage will be 0 percent (100 percent).

*Compset Similarity, Strategic Groups-Manager* compares the strategic groups compset to a hotel’s manager-generated compset. The similarity between these two sets is computed as the number of elements in the intersection of the sets divided by the number of elements in their union. In other words, if the manager-generated set consists of {1, 2, 3, 5, 8} and the strategic groups set consists of {2, 3, 4, 5, 6, 7}, their union is {1, 2, 3, 4, 5, 6, 7, 8} and their intersection is {2, 3, 5}. *Compset Similarity* is then  $3/8 = 0.375$ , or 37.5 percent. If two compsets are identical, *Compset Similarity* is 1.0. At the other extreme, if two compsets are completely different, *Compset Similarity* is 0.0. Our other similarity construct, *Compset Similarity, Customer-Manager* compares the customer-generated compset to a hotel’s manager-generated compset.

4.6.3. Independent variables: controls

Additional variables are included in the models to control for location- and business-specific differences that may impact hotel performance. *Scale* is a proxy for hotel quality as this may impact ADR and RevPAR (Anderson et al., 2000; O’Neill and Mattila, 2006). Three dummy variables identify the four chain scales in our study (Luxury, Upper-Upscale, Upscale and Upper-Midscale). *Tract* is the nine distinct tracts and eight dummy variables identify each specific area. Location has an impact on ADR as different geographical areas have different hotel rate potentials (Bull, 1994). *Operation* is the type of business model the hotel operates as (i.e., Chain Management, Franchise or Independent). Research has shown that branded hotels with a good brand reputation obtain higher ADRs and higher occupancies (O’Neill and Mattila, 2006, 2010). Two dummy variables uniquely identify the type of business model. *Quality* is the average of a hotel’s 2010–2012 satisfaction scores gathered from the TripAdvisor web site. We include this measure as a proxy for management quality. That is, hotels with superior quality ratings are likely to have better management that we believe will have, in turn, superior revenue management. *Market Concentration*, measured by the Herfindahl-Hirschman Index (HHI), is the sum of the squared market shares of firms in a market. Since competition is local, and since an upper-midscale hotel is not really competing with an upper-upscale hotel in a different tract, HHI is computed for each combination of hotel class and geographic area. We use market concentration to control for the fact that hotels operating in markets

**Table 2**  
Descriptive Statistics.

Variable	N	Mean	Std.Dev.	Minimum	Median	Maximum
ADR	312	122.23	51.04	56.93	106.82	387.32
RevPAR	312	85.29	42.24	16.27	73.75	272.46
Reciprocal Monitoring	312	55.35	60.00	0.00	60.00	100.00
Market Concentration	312	878.34	608.67	397.00	576.00	3180.00
Quality Score	312	4.07	0.39	2.50	4.12	4.73
Strategic Groups Similarity	312	14.50	14.02	0.00	10.00	83.33
Customer Similarity	312	23.62	15.66	0.00	20.00	83.33

that are less competitive will have, *ceteris paribus*, the opportunity to raise prices while achieving higher occupancy rates.

**5. Results**

**5.1. Descriptive statistics**

Descriptive statistics for the sample are provided in Table 2. Chain hotels are 92% of our sample, these being either franchised or managed under a management agreement. Hotels range in size from 21 to 2,019 rooms, with a mean of 224.9 rooms and a standard deviation of 222.0 rooms. There are 16 luxury hotels (5.1%), 79 upper-upscale hotels (25.3%), 94 upscale hotels (30.1%) and 123 upper-midscale hotels (39.4%). With the broad range of hotel types, financial measures exhibit wide ranges. ADR has a mean of \$122.23, with a minimum of \$56.93 and a maximum of \$387.32. A median of \$106.82 indicates that a majority of hotels are in the lower price range, with Upper Upscale and Luxury hotels achieving high rates. RevPAR ranges from \$16.27 to \$272.46, with a mean (median) of \$85.29 (\$73.75). Mean monitoring reciprocity is 55.35%, meaning that about half of a firm’s compset are, in turn, monitoring the firm. With a range from 0% to 100%, there are vast differences in monitoring behaviors. HHI, our measure of market concentration, has a mean of 878.34 with the minimum (maximum) being 397 (3,180). The U.S. Department of Justice considers a market to be moderately concentrated when HHI is between 1,500 and 2,500 (Department of Justice, 2018). A highly concentrated market is one with an HHI above 2,500. With only 14 hotels in highly concentrated markets, 95 percent of the hotels in our sample are facing competitive conditions. Online review quality scores ranged from 2.50 to 4.73, with a mean (median) of 4.07 (4.12). Overall customer satisfaction is quite high. Sizes for the *manager-generated* compsets range from four to twelve competitors. The median compset size was six, with 36.74% of hotels having a set of this size. The mean was slightly higher at 6.52 competitors. The *Compset Similarity* scores were surprisingly low, with means of 14.50 and 23.62 percent for the Strategic Groups-Manager and Customer-Manager sets, respectively.

**5.2. Reciprocity and financial performance (H1)**

Hypothesis 1 predicts that firms with a high degree of reciprocal monitoring have greater financial performance. To test this hypothesis, we use the regression models described above with the dependent variable as ADR in one model, and with RevPAR as the dependent variable in a second model. Regression diagnostics indicated 22 outliers in both models. Observations exceeding common cutoff values for leverage (hat value > 2.5p/n), Cook’s (1977) distance (4/n) and studentized residuals (> |3|) were excluded from final regressions. Outliers were present in most tracts (slightly more in the downtown core) and all types (however, about 60 percent were luxury hotels). The reduced sample results were qualitatively similar to the full sample and final regression diagnostics were good. This procedure was followed for all subsequent models. With 81 percent of luxury hotels dropped from the final ADR model (and a similar figure for the RevPAR model), our

**Table 3**  
Results, H1.

Variable	Predicted Sign	Dependent Variable	
		ADR	RevPAR
Reciprocal Monitoring	+	8.192*** (3.09)	3.966 (3.09)
Market Concentration	+	0.002 (0.00)	0.001 (0.00)
Quality Score	+	12.988*** (2.70)	13.488*** (2.79)
Controls			
Scale		Yes	Yes
Tract		Yes	Yes
Operation		Yes	Yes
Constant		141.018*** (15.56)	67.99*** (14.98)
Observations		290	290
R-square		0.868	0.856
F Statistic (df = 16; 273)		111.876***	101.225***

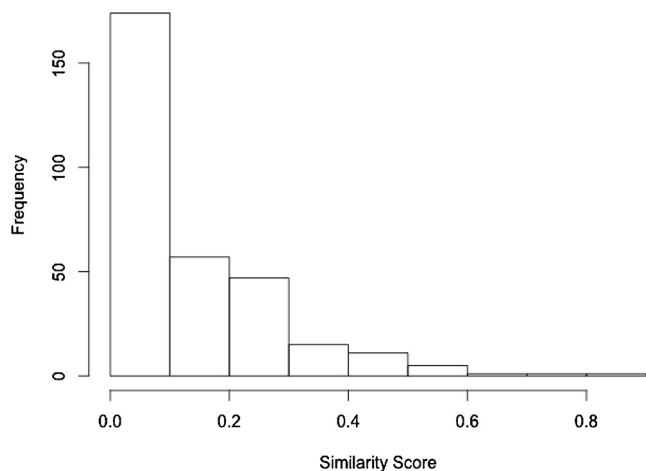
Note: Standard errors in parentheses. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01, respectively (one-tail for variables with predicted signs). For brevity, tract, type and class dummies are not presented.

results may not generalize to luxury hotels (recall, though, our results were qualitatively similar). Our models account for a very high proportion of variance (0.87 and 0.86) in both dependent variables. Our hypothesis is supported for ADR, as the coefficient on *Reciprocal Monitoring* is significant (p < 0.01) in the ADR model. Table 3 contains unstandardized coefficients for both models. The coefficient of 8.192 means that a 10 percent increase in monitoring reciprocity would result in an \$0.82 increase in ADR. For the mean hotel with 225 rooms and 80 percent occupancy, a rate increase of \$0.82 would result in a revenue increase of \$53,874. A non-significant positive coefficient for the RevPAR model suggests total revenue is not increasing. While this doesn’t seem to support H1, no change in revenue with a rate increase must lower occupancy, a mechanism that results in higher profit through a decrease in total variable costs (e.g., lower housekeeping hours, less energy and amenities consumption on lower volume). Considering both models, we conclude that higher monitoring reciprocity results in greater financial performance. Since hotels obtain higher ADR and – through lower occupancy – higher profit per available room, financial performance is better. Therefore, Hypothesis 1 is supported.

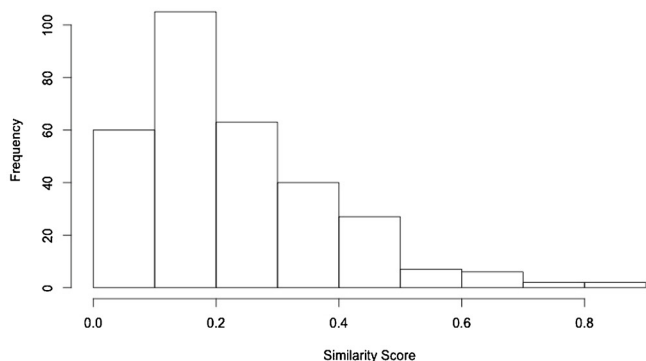
**5.3. Deviation of manager-generated sets (H2)**

Hypothesis 2 predicts that manager-generated compsets (i.e., the actual compset) differ from both strategic groups compsets and customer-generated compsets. Our test for hypothesis 2 is a t-test that *Compset Similarity*, *Strategic Groups-Manager* and *Compset Similarity*, *Customer-Manager* is significantly different from unity (1.0, or 100 percent). Strategic groups-based and manager-generated compsets had a mean similarity of only 14.50 percent. The distribution of similarity scores is shown in Fig. 1, Panel A. A maximum similarity of 83.33 percent means that no hotel has the same competitors between the two different sets. Surprisingly, 71 of the 312 hotels (23 percent) had no similarity between their strategic groups-based and manager-generated compsets. The mean similarity score for customer-generated and manager-generated compsets was 23.62 percent. While much higher than that of the *Strategic Groups-Manager* similarity score, this percentage is still a remarkably small overlap in compsets. The distribution of similarity scores for these two sets is shown in Fig. 1, Panel B. Here, too, there are no hotels that had matching compsets (i.e., the maximum similarity score was 83.33 percent) while only 16 hotels (5 percent) had no overlap in competitors. T-tests support our hypothesis that the manager-generated compsets differ from both strategic groups and

**Panel A: Strategic Groups and Manager-Generated Sets**



**Panel B: Customer-Generated and Manager-Generated Sets**



**Fig. 1.** Similarity Score Distributions.

Panel A: Strategic Groups and Manager-Generated Sets.

Panel B: Customer-Generated and Manager-Generated Sets.

customer-generated compsets ( $t = 3.53, p < .05$ ).

**5.4. Performance impact of deviation from strategic groups-based sets (H3)**

Hypothesis 3 is tested using the regression model specified in section 4.4 above. Our hypothesis is that managers' deviation from strategic groups-based competitive sets results in lower financial performance. With compset similarity expressed as a proportion, the significant coefficient of 15.170 ( $p < .05$ ) for ADR means that a 10 percent deviation (i.e., decreasing similarity) in the compset would result in a \$1.52 decrease in ADR. See Table 4. In other words, firms appear to have higher performance if their compsets are better aligned with strategic groups-based compsets. A positive, marginally significant coefficient ( $p < .10$ ) in the RevPAR model also finds that total revenue is adversely affected by managers' deviation from strategic groups-based compsets. As with Hypothesis 1, a non-significant or marginally significant coefficient coupled with a rate increase must have lower occupancy which, through lower variable cost, improves financial performance. Therefore, Hypothesis 3 is supported.

**5.5. Performance impact of deviation from customer-based sets (H4)**

Our final hypothesis predicts that managers' deviation from customer-based compsets will result in lower financial performance. A significant, positive coefficient for the ADR model and a positive – but not significant – coefficient in the RevPAR model supports our hypothesis; as in H1, higher ADR coupled with lower occupancy, likely

**Table 4**  
Results, H3.

Variable	Predicted Sign	Dependent Variable	
		ADR	RevPAR
Compset similarity to strategic groups	+	15.17** (7.46)	10.198* (7.17)
Market Concentration	+	0.002 (0.00)	0.001 (0.00)
Quality Score	+	11.929*** (2.71)	12.475*** (2.64)
Controls			
Scale		Yes	Yes
Tract		Yes	Yes
Operation		Yes	Yes
Constant		157.511*** (16.56)	71.897*** (14.44)
Observations		291	289
R-square		0.86	0.851
F Statistic (df = 16; 269)		105.535***	96.966***

Note: Standard errors in parentheses. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ , respectively (one-tail for variables with predicted signs). For brevity, tract, type and class dummies are not presented.

**Table 5**  
Results, H4.

Variable	Predicted Sign	Dependent Variable	
		ADR	RevPAR
Compset similarity to customer-based groups	+	11.249** (6.13)	0.973 (6.11)
Market Concentration	+	0.002 (0.00)	0.002 (0.00)
Quality Score	+	12.465*** (2.69)	12.289*** (2.76)
Controls			
Scale		Yes	Yes
Tract		Yes	Yes
Operation		Yes	Yes
Constant		145.599*** (15.43)	68.286*** (14.91)
Observations		292	293
R-square		0.866	0.848
F Statistic (df = 16; 275/276)		110.746***	96.282***

Note: Standard errors in parentheses. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ , respectively (one-tail for variables with predicted signs). For brevity, tract, type and class dummies are not presented.

results in higher profits. See Table 5. Examining both coefficients for compset similarity (ADR and RevPAR) suggests that there are only modest penalties for managers who choose compsets that differ from the customer choices. A 10 percent increase in similarity would result in a modest ADR increase of \$1.12 per room rented, an increase that must be offset by modest declines in occupancy as total revenue is unchanged. With lower volume on unchanged revenue, profits are likely to be higher, leading us to conclude that H4 is supported.

**5.6. Robustness checks**

Since the strategic groups-based competitive set is constructed based on hotel attributes, a question arises whether our results are sensitive to changes in: (1) the weights used to compute the similarity score and, hence, determination of the strategic groups compset; and, (2) the chosen size of the strategic groups-based competitive set.

To address the first item, we examined several regression models that used different weights for the Compset similarity score. The first such

**Table 6**  
Results, Robustness to Alternative Strategic Groups-Based *Compset Similarity* Weights.

Variable	Predicted Sign	Compset Similarity Weighting Alternatives					
		Baum and Lant (2003)		Proposed Alternative		Size Only	
		ADR	RevPAR	ADR	RevPAR	ADR	RevPAR
<i>Compset similarity, strategic groups</i>	+	18.429*** (7.18)	12.608** (6.95)	33.162*** (7.86)	22.865*** (7.79)	5.593 (15.24)	14.74 (14.96)
<i>Market Concentration</i>	+	0.002 (0.00)	0.001 (0.00)	0.000 (0.00)	0.000 (0.00)	0.002 (0.00)	0.002 (0.00)
<i>Quality Score</i>	+	11.917*** (2.71)	12.229*** (2.66)	10.588*** (2.62)	12.6*** (2.64)	12.037*** (2.66)	12.408*** (2.70)
Controls							
Scale		Yes	Yes	Yes	Yes	Yes	Yes
Tract		Yes	Yes	Yes	Yes	Yes	Yes
Operation		Yes	Yes	Yes	Yes	Yes	Yes
Constant		143.177*** (15.47)	70.313*** (14.52)	158.842*** (16.02)	62.305*** (14.15)	132.999*** (19.10)	72.355*** (14.69)
Observations		291	290	286	286	287	288
R-square		0.865	0.85	0.872	0.857	0.848	0.845
F Statistic		110.118***	96.778***	114.661***	100.976***	94.489***	92.59***

Note: Standard errors in parentheses. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ , respectively (one-tail for variables with predicted signs). For brevity, tract, type and class dummies are not presented.

model used the empirical weights obtained by Baum and Lant (2003) in their study of Manhattan hotels. Relative to the naïve model weights, their model placed greater weight on location, shifting the weight almost entirely from price. With the Baum and Lant weights, results for *Compset similarity, strategic groups* strengthened for both ADR and RevPAR. See Table 6. That is, a deviation by managers from this strategic groups compset would result in a more rapid decline in hotel performance. A second model was based on the experience of one of the authors of this study. Having worked for two years with the executive leadership at a major hotel chain, and talked with numerous managers, we established weights that put greater weight on location, shifting emphasis entirely from hotel size. These results were even stronger, with large, positive and significant coefficients for the ADR and RevPAR models. Since these alternative set constructions support H3, we conclude our results are not sensitive to the weights used in our hypothesis test. To contrast these results to a nonsensical model, we examined a model where the strategic groups-based compset was selected entirely on the basis of hotel size. The results were telling: There was no significant impact when managers had deviated from this strategic groups compset. Further, and in sum, the choice of weights applied in constructing the strategic groups compset does matter. But unless the weights are nonsensical, there is an adverse impact from managers' deviation from the strategic groups compset.

Finally, we examined the sensitivity of our results to changing sizes of the strategic groups-based compsets. Recall that we limited the strategic groups-based size to six hotels to match the median and modal size of the manager-generated compsets. Untabulated results indicated that our results are robust to our specification, holding for varying sizes of strategic groups- and customer-based compsets. This conclusion appears to be so because hotel rates are fairly homogeneous within combinations of tract and class; that is, a hotel would gain few insights from increasing a strategic groups-based compset from, say, 6 hotels to 10 hotels.

5.7. Post hoc analyses

Our theory led to hypotheses (H3 and H4) that deviating from the strategic groups-based and customer-based compsets would have an adverse impact on performance. Overall, our findings are consistent with the idea that a manager-generated compset bearing greater similarity (i.e., less deviation) to these other compsets results in improved

performance. Seeking to better understand these results, we conducted some *post hoc* analyses.

Our models support the idea that strategic factors (e.g., price, size and location) and customer preferences must be taken into account by managers developing compsets. We believe that “best-fit” competitors are likely to appear in all three compsets. And “worst-fit” competitors are likely to be those that are in the manager’s compset, but not appearing in either the strategic groups- or customer-based sets. Consider a Venn diagram. Fig. 2 shows three compsets: Manager-generated, customer-based and strategic groups-based. In this example, the manager-generated set has twelve competitors (maximum in our sample), the strategic groups set has six competitors and the customer-based set, 10. With three hotels in both manager-generated and strategic groups-based sets, commonality is 0.200 (i.e., 3 common hotels/15 total hotels). With two hotels in common between the customer-based and manager-generated sets, commonality is 0.118 (i.e., 2 common/17 total). We are interested in assessing how the manager-generated set compares to the other two compsets and how a manager might have responded to strategic groups factors and customer preferences. The Venn diagram reveals that one hotel is in all three sets (area A). In the regression model we describe below, this is our baseline. Further, one competitor is common only to the customer- and manager-generated sets (B; although they have two in common, the other competitor is the one in all three sets). Finally, we see that two competitors are only in both strategic groups- and manager-generated sets (C; again, they share three, but two are shared exclusively). It is possible to compute proportions of the manager-generated compset into four categories: (1) 8.3 percent are shared by all three sets; (2) 16.7 percent is shared only with the strategic-based set; (3) 8.3 percent shared only with the customer-based set; and, (4) 66.7 percent of the manager’s set as unique.

Relative to the base case, a hotel with a high proportion of competitors in the manager-generated set that have nothing in common (i.e., 8 in our example) with the other two sets should have much lower performance. Similarly, higher proportions that are solely in the customer-manager overlap, or the strategic groups-manager overlap, should also result in lower performance. To examine the relationship between overlaps and performance, we estimated the following model:



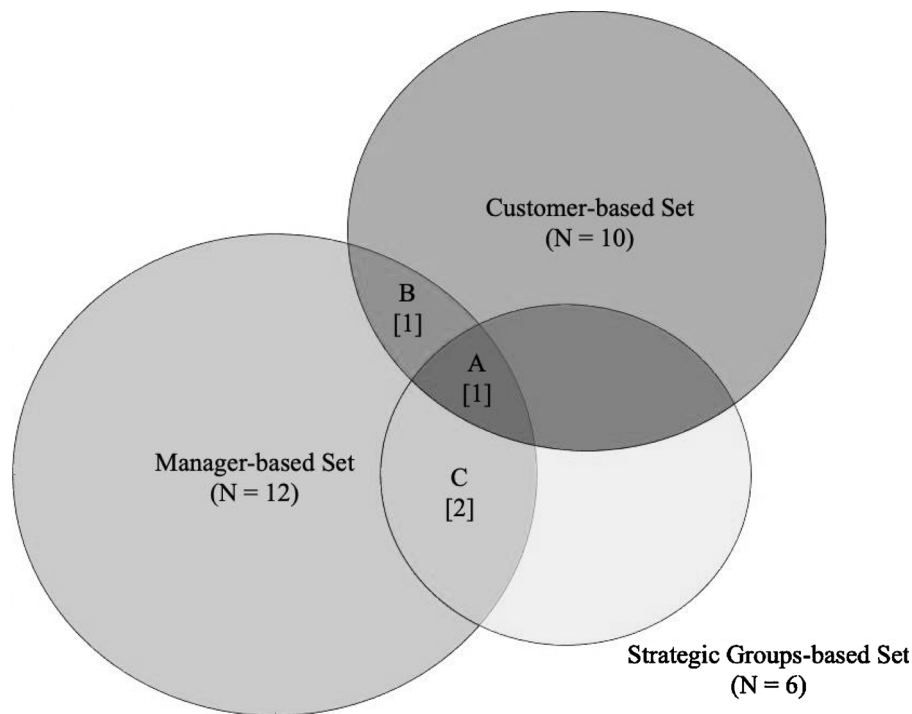


Fig. 2. Venn Diagram.

$$\begin{aligned}
 Performance_i = & \beta_0 + \beta_1 Proportion Unique + \beta_2 Proportion SG \\
 & + \beta_3 Proportion CB + \beta_4 Market Concentration \\
 & + \beta_5 Quality + \sum_{q=2}^4 \gamma_q Scale + \sum_{i=2}^9 \xi_i Tract \\
 & + \sum_{i=2}^3 \lambda_i Operation + \varepsilon_i
 \end{aligned} \tag{4}$$

where  $Performance_i$  is *ADR*, *RevPAR* and occupancy (i.e., rooms rented divided by rooms available) for hotel  $i$ . *Proportion Unique* is, as described above, the proportion of the manager’s compset that is not shared with the other two compsets (i.e., these hotels are unique). *Proportion SG* is the proportion of the manager’s compset that is also shared with the strategic groups-based compset (but *not* including hotels also shared with the customer-based set). Finally, *Proportion CB* is the proportion of the manager’s compset that is exclusively shared with the customer-based set. In a regression model fit with an intercept, our model specification means that the baseline case is *the overlapping case* (i.e., the proportion of a manager’s compset that is also present in the other two sets).

Our results (Table 7) are interesting. We found that when the manager’s compset contains little overlap (i.e., *Proportion Unique* is relatively large), *ADR* declines ( $b_1 = -0.130, p < .05$ , one-tail). Occupancy is marginally significant and positive ( $b_1 = 0.053, p < .05$ , one-tail), a result likely brought about by a lower *ADR*. The overall effect on revenue (i.e., *RevPAR*) is marginally significant with a one-tail test ( $b_1 = -0.084, p < .10$ ), suggesting that the rise in occupancy is not sufficient to overcome the decline in *ADR*. As a practical matter, for a hotel able to reduce the number of “unique” hotels in its compset by 20 percent, *ADR* should increase \$2.60. For a 225-room hotel with 70 percent occupancy, this rate increase would translate into approximately \$150,000 in additional annual revenue (assuming occupancy remains about the same). Somewhat surprising to us is that none of the coefficients for *Proportion SG* are significant. In other words, a higher proportion of hotels in a manager’s compset that are shared only with the strategic groups-based set appears to have no impact on rate, occupancy or total revenue. Finally, increasing the proportion of hotels

Table 7 Results, Post-Hoc Analysis.

Variable	Predicted Sign	Dependent Variable		
		ADR	RevPAR	Occupancy
Proportion Unique	-, -, +	-0.13** (-0.06)	-0.084 (-0.06)	0.053* (0.03)
Proportion SG	-, -, +	0.031 (0.10)	0.049 (0.10)	0.002 (0.05)
Proportion CB	-, -, +	-0.106* (-0.06)	-0.117* (-0.06)	0.001 (0.03)
Market Concentration	+	0.001 (0.00)	0.001 (0.00)	0.002* (0.00)
Quality Score	+	11.797*** (2.75)	12.447*** (2.75)	5.211*** (1.57)
Controls				
Class		Yes	Yes	Yes
Tract		Yes	Yes	Yes
Management		Yes	Yes	Yes
Constant		156.496*** (12.38)	73.375*** (15.42)	37.129*** (8.00)
Observations		281	285	291
R-square		0.871	0.855	0.44
F Statistic (df = 18; 267/266/272)		100.065***	86.802***	11.875***

Note: Standard errors in parentheses. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ , respectively. For brevity, tract, type and class dummies are not presented.

shared with the customer-based compset (*Proportion CB*) results in significantly lower rates and *RevPAR* ( $b_3 = -0.106$  and  $-0.117$ , respectively,  $p < .05$ , one-tail). Recall that, since our baseline is the overlap of all three compsets, an increase in *Proportion CB* comes at “the expense of” choosing hotels for which there is common agreement. The magnitude of the *ADR* coefficient is less than that of *Proportion Unique* and “sacrificing” a hotel in the common set for *Proportion CB* is, therefore, less damaging to the firm. Since occupancy does not increase to offset the decline in rate, the impact on *RevPAR* is, therefore, greater than for *Proportion Unique*.

These analyses reinforce the notion that getting the compset “right” is of paramount importance to the firm. Multiple perspectives appear to

provide useful information to managers selecting compsets.

## 6. Discussion

Our evidence suggests that the degree of monitoring reciprocity and similarity between compsets does have an economically significant, positive impact on financial performance. ADR and profit are positively influenced by increasing the degree of reciprocal monitoring. While positive, the coefficient in our RevPAR model was not significant. This suggests that increasing reciprocity drives higher rates and lower resulting occupancy, without an adverse impact on total revenue. At the very least, lower occupancy will result in lower total cost (through lower total variable cost) and, therefore, higher profits. There is one issue affecting reciprocity: A hotel may have lower reciprocity not because of any action on their part (i.e., they are selecting the “right” competitors), but because one or more competitors may be incorrectly identifying their competitors. In other words, reciprocity can be lowered by identification mistakes made by a firm’s competitors. However, while we have no direct evidence, we do not believe this is a systematic problem. If this were a serious, systematic problem, we would not find any evidence of a relationship between monitoring reciprocity and performance.

Our study also suggests that the best way to create compsets is by using a strategic groups-based approach or, perhaps to a lesser extent, identifying customers’ consideration sets (and the competitors satisfying those sets). The customer-based and strategic groups-based compsets, however, have a mean similarity percentage of only 13.8 percent. This means the different approaches result in two different compsets. In our two models, the larger coefficient of the strategic groups-based compset appears to dominate. Given that customers are ultimately the ones who make purchase decisions, we were surprised by this outcome. Perhaps customer online search patterns are not capturing their consideration sets and our results are due to measurement issues.

In terms of managerial implications, the mean reciprocity percentage of 55 percent suggests that managers struggle with identifying relevant competitors. Alternatively, managers may be selecting compsets comprised of hotels that are not really their competitors (e.g., lower scale hotels with lower RevPAR or lower quality hotels, also with lower RevPARs). Such deliberate misidentification could be the result of using compset financial performance as a benchmark in the general manager’s incentive compensation plan. Our study is not able to examine the reasons for misidentification, but our results are compelling in documenting the consequences of misidentification.

To highlight the economic importance of accurate competitor identification, Fig. 3 depicts the predicted increase in profit for a range of hotel sizes and monitoring reciprocity. While we do not have cost or profit data, a price increase is likely to come with no increase in costs. Accordingly, an ADR increase of \$0.082 per rental (i.e., the coefficient in Table 3) would amount to a profit increase of \$0.082 per rental. As we center our model on the mean of monitoring reciprocity, Fig. 3 shows that profit decreases if the reciprocal monitoring percentage falls below the current average of the sample of 55 percent. A reciprocity percentage higher than the mean leads to a rapid increase in profitability.

Not only do managers struggle with accurately identifying competitors, but they also select compsets that have low similarities to both strategic groups-based and customer-based compsets. The similarity percentage between manager-generated and customer-based compsets of only 24 percent highlights the fact that managers seem to be unable (or unwilling) to determine the criteria their customers care about when booking hotels. This likely results in pricing mismatches when prices are modeled after hotel properties that customers do not even see as competitors, but may also impact other operating decisions, such as marketing campaigns.

The financial impact, based on our models, is huge. For example, if a

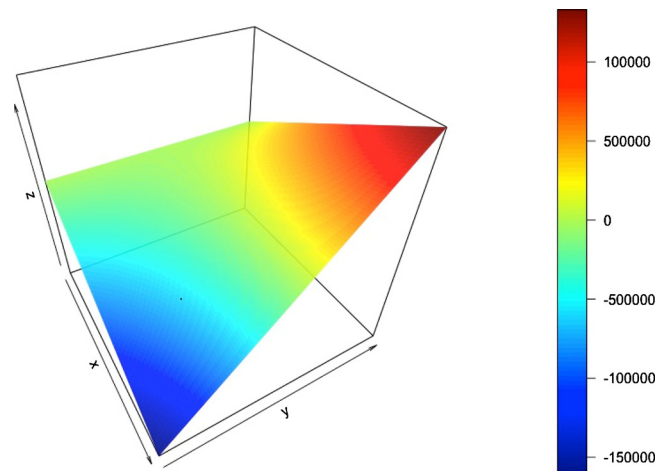


Fig. 3. Profit Impact, Monitoring Reciprocity.

Note. The x-axis corresponds to hotel size and the y-axis corresponds to monitoring reciprocity. With a regression coefficient of \$0.082/1 percent change in monitoring reciprocity, total incremental profit is a function of rooms rented. Rentals are, of course, a function of hotel size and occupancy. While rentals would seem to be the proper axis, size better conveys profit potential. The z-axis is profit change, obtained from:  $Profit = 0.082 \times (Monitoring\ Reciprocity - 55) \times Size \times 365$ . This is because a price increase does not affect total costs. This formula centers the profit calculation on the mean monitoring reciprocity, with the graph depicting reciprocity below (above) the mean as a decline (rise) in annual profit. For a 1000-hotel with complete monitoring reciprocity, profit would increase approximately \$1.35 million. Conversely, a 25-room hotel with zero reciprocity would see profits decline by \$41,000.

hotel manager were to increase their strategic groups similarity from the mean of 14.5 percent to, say, 80 percent, our model suggests that RevPAR would increase by  $\$10.198 \times (0.800 - 0.145) = \$6.68$ . For the mean hotel size of 225 rooms, this would result in an annual revenue increase of \$548,595 ( $\$6.68/\text{available room} \times 225 \text{ available rooms} \times 365 \text{ days/year}$ ). And since costs do not increase, profits increase by the same amount.

## 7. Conclusion

While research has shown that accurate competitor identification leads to better financial performance (Clark, 2011; Lee, 2015), our study appears to be the first to investigate the financial performance consequences that stem from inaccuracies in the compset chosen by management. We found that reciprocal monitoring was positively associated with ADR. The magnitude of the monitoring reciprocity – financial performance associations are economically significant, as demonstrated in Fig. 3. We further demonstrate that managers deviate from both strategic groups-based and customer-based compsets, a finding that supports prior studies that suggest a significant mismatch between different types of compsets. These deviations are associated with lower levels of financial performance. That is, greater similarity in compsets results in better financial performance. We make contributions to the existing competitor identification literature by demonstrating that accurate competitor identification results in better financial performance, an idea long suggested by strategy researchers (e.g., Clark, 2011). Additionally, it highlights the economic effect of increasing compset reciprocity, and similarity to strategic groups-based and customer-based compsets.

### 7.1. Limitations

First, with one year of data, our models could not be tested to see if the influence of monitoring behavior on financial performance varies over time. Our second limitation concerns the measurement of distance

between competitors. Baum and Lant (2003) define the location of a hotel property on the Street-Avenue grid of New York City. We attempted to assess distance between hotels, but distance is problematic in a large, diverse metropolitan setting. For example, a distance of 3 miles in the downtown core could translate into a commute time of more than one hour during rush hours. Conversely, a distance of 3 miles at a suburban location could be 3–10 min of travel time at all hours. Furthermore, some hotels a mile from a downtown hotel could be in a high-crime, gang-controlled neighborhood that few customers (and hotels) might consider competitors based on distance. Another issue was what time(s) should be considered when calculating commute length? In sum, while our approach (tracts) is a crude measure, a sample of compsets showed reasonable choices using our modified Baum and Lant (2003) algorithm. We examined alternative weighting schemes and found those results to be qualitatively similar to those reported here. The Baum and Lant study, focused on the small island of Manhattan, nevertheless suffers most of the issues we faced (e.g., cross-town travel can take a very long time whereas uptown/downtown travel is quite fast even during rush hours, an important factor unaccounted for in their algorithm). Finally, Baum and Lant (2003) asserted that managers, regardless of experience, make mistakes when identifying competitors. A third limitation of our study concerns the lack of insight into the decisions about compset formation. We do not have survey data regarding who makes compset decisions. But while our study has actual paid-for monitoring data (in contrast to Baum and Lant's unverified survey data), we cannot rule out that managers seek out and use additional information from other sources. However, managers' use of supplemental monitoring data would likely work against us finding results. A fourth limitation concerns the generalizability of our results. While our choice of a large metropolitan area likely improved on the generalizability concerns of prior studies, our results may not generalize to smaller markets (e.g., Tucson, Boise or Roanoke) or to the segments we excluded. To the latter point, we note that economy and midscale hotels are only 11% of total market revenue. In other words, our sample comprises and overwhelming proportion of the total market. Lastly, we constructed the customer-based compset from web browsing activity of consumers on a travel website. While we are familiar with the study market and evaluated the sets for reasonableness, we cannot know whether viewing behavior resulted in customer purchases or just random browsing.

## 7.2. Future research

Our findings suggest a higher economic impact and higher significance of reciprocal monitoring behavior and of compset similarity for ADR than for RevPAR. As mentioned, this could be due to the mediating influence of occupancy rates on RevPAR. Further research is needed to determine whether this assumption is true or if other factors are at play. Another potential line of research would be to model the impact that selecting the wrong competitors has not only on financial performance, but also on customer satisfaction, the effectiveness of marketing campaigns, and other variables.

## Declaration of Competing Interest

None.

## Acknowledgment

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