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Judgmental adjustments in revenue management : exploring the impact of user overrides on the accuracy of system-generated occupancy forecasts at multiple forecasting horizons

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Chapter 1

Introduction

Prediction is very difficult, especially if it's about the future.

- Niels Bohr -

1.1 Background and Scope of the Research

Revenue Management (RM) is a systematic approach to optimizing revenues by setting prices and managing product availability based on patterns of demand and customer willingness to pay (Talluri & Van Ryzin, 2004). It was initially introduced in the airline industry, where it became “an integral part of commercial operations for virtually all airlines” (Cross, Higbie, & Cross, 2011, p. 10). Boyd (1998) analyzed the impact of RM at US Airlines and Delta Airlines and credited it with US\$500 million and US\$300 million of increased revenue, respectively. After the enormous success of RM in the airline industry, it was adopted by the hotel industry. Revenue management brought US\$100 million of additional annual revenue to Marriott Hotel (Cross, 1997b).

Today, many other industries seek benefits from RM techniques and approaches, among these are cruise lines, restaurants, golf courses, the sports and entertainment industries, television networks, transportation firms, and natural gas storage and transmission (Talluri & Van Ryzin, 2004). RM famously helped National Car Rental to avert bankruptcy thereby safeguarding 7500 jobs (Geraghty & Johnson, 1997). According to FedEx Chairman and CEO Frederick Smith, “a significant portion of their 10 per cent revenue increase and 33 per cent growth in profits” can be attributed to RM and the pricing approach (Cross et al., 2011, p. 13).

RM includes a revenue optimization methodology that uses data and analytics to anticipate customer behavior and optimize price and product availability. It helps companies in certain industries to drive their revenues and profits. Essential

characteristics that these service industries all share, are constrained capacity, perishable inventory, reservations made in advance, and a segmentable market (Kimes, 1989, 2003).¹

The birth of RM in the airline industry is commonly attributed to the following three key turning points: (1) the creation of the Littlewood rule² in 1972; (2) the introduction of the US Domestic Deregulation Act of 1978; and (3) the doctoral thesis by Peter Belobaba (*Air Travel Demand and Airline Seat Management*) which introduced the concept of Expected Marginal Seat Revenue (EMSR) in 1987 (Yeoman, 2011; Yeoman & McMahon-Beattie, 2017). While these turning points were undoubtedly important, technology played a crucial role in shaping modern RM and was the main enabler of the vast majority of these turning points. Indeed, the Littlewood rule was significant as it established the first static single resource-based RM model. However, successful implementation of the Littlewood algorithm was feasible due to a favorable pre-condition. Prior to 1972, British Overseas Airways Corporation introduced a sophisticated computer reservation system (Yeoman & McMahon-Beattie, 2017). Similarly, although the US Domestic Deregulation Act changed the face of the airline industry forever by allowing entrance of Low-Cost Carriers (LCCs), the resulting changes were possible due to the advanced state of technology. In 1985, American Airlines responded to increased competitive pressure from a highly competitive LCC - PEOPLExpress by using advanced analytics and introducing the Ultimate Super Saver. Due to the newly developed computer systems, it was able to control the availability of deeply discounted fares. This important advantage helped American Airlines to drive PEOPLExpress out of business (Yeoman & McMahon-Beattie, 2017). Moreover, EMSR had a significant impact on businesses because it became feasible to implement and build its logic into the foundation of many revenue management systems. In other words, technology played an important role in all three turning points, and it continues to play an important role in current RM development.

Technology has been paramount not only for the development of airline RM, but also for hotel RM, and its importance is still growing. Marriott is often associated with pioneering the RM concepts in the hotel industry. For example, it first experimented with rate fences and length of stay controls (Hanks, Cross, & Noland, 2002; Kimes, 2016). In the mid-1980s, Marriott developed its own automated RMS,

which generated daily demand forecasts and inventory recommendations for each of its 160,000 rooms at its Marriott, Residence Inn and Courtyard brands (Marriott & Cross, 2000). Hilton, Holiday Inn and Sheraton and other major hotel chains in North America followed Marriott's example (Cross et al., 2011). In the late 1980s, many hotels with sophisticated electronic property management systems introduced yield management systems (Kimes, 1989). Since the 1990s, the hotel industry has experienced many drastic changes and pressures: 1) price transparency leading to the shift of balance towards consumer power; 2) the rise of Online Travel Agents (OTAs) resulting in increased distribution costs; 3) changing ownership structures leading to the need to generate revenues from all departments; 4) the tragic events of 9/11 which resulted in a hotel occupancy decrease of 15-20% and a decrease in profits for US hotels by more than \$600 million. During these shifts and turbulent times, evolving technological capabilities represented an important competitive advantage. In the late 1990s, Cross (1997a) highlighted the role of technology in RM, emphasizing the importance of forecasting and optimization components of a revenue management system. At the same time, there was growing awareness that an RMS would become one of the main weapons to win this battle. Kimes and Wagner (2001) emphasized the importance of revenue management systems and called for protecting it as a trade secret. Overall, a shift can be observed towards the increasing power of science, and a dominance of technology and complex algorithms.

Although technology plays an increasingly important role, it cannot operate without human input. In 1992, Jones and Hamilton (1992, p. 91) warned about an excessive emphasis and reliance on yield management systems: "no computerized system will ever be successful without a wide range of skilled personnel who are involved in the process." Similarly, a decade later, Kimes (2003, p. 138) stated that the "mere possession of a revenue management system does not guarantee success." Despite increased technological developments, this view has been supported in more recent studies. Bobb and Veral (2008, p. 299) warned that, "revenue management applications and software cannot, and should not, be seen as only a computerized solution but rather as a tool to aid the human decision-making process. In fact, a hybrid system may prove to be the most effective economically as well as managerially." For example, in the context of automated room rate pricing decision-making, Van der Rest and Roper (2013) and Van der Rest, Roper, and Wang (2018) stressed the importance of human and social capabilities. In the context of hotel occupancy forecasting, human judgement plays an important role as many algorithms are based on historical data, which do not include present and future changes and may not predict a discontinuous change in the business environment (Ghalia & Wang, 2000). Revenue managers often possess important additional knowledge, exogenous to the RMS (Schwartz, Uysal, Webb, & Altin, 2016). For these

¹ Segmentation is a key characteristic of revenue management. It allows the strategy to be tailored to match the needs of various customers and to increase bookings, revenue and profit. Segmentation can be done in various ways and with various degrees of data aggregation. A first step and common approach is to distinguish between transient and group business. Group business is "typically defined as 10 or more rooms per night, sold pursuant to a signed agreement" (STR, 2019). The transient segment are "guests who book individually rather than with a group" (IDeaS, 2019).

² The first static single resource quantity based RM model developed by Ken Littlewood.

reasons, RM has been referred to as the ‘art and science’ of forecasting demand, while simultaneously adjusting price and availability of inventory to meet demand (Cross, Higbie, & Cross, 2009; Erdem & Jiang, 2016; Josephi, Stierand, & Van Mourik, 2015).

There is general consensus on the importance and need for more work on the role of human judgment in technology-supported RM decision-making. For example, in a review of academic journal articles, books and monographs published in the period 2002–2012, Ivanov and Zhechev (2012) concluded that RM technology is important, but far too little attention was paid to its impact on RM decisions. Also, after systematically reviewing 163 studies (from 2004–2013) using three major online hospitality and tourism research databases, Denizci Guillet and Mohammed (2015, p. 546) argued that, “there are still unanswered questions about the interaction of users with technology regarding the impact of user overrides.” Similarly, Josephi et al. (2015, pp. 4-5) who provided a brief historic overview of RM, pointed out that, “future avenues for research should explore the role of automation and human judgment in RM decision making.” Despite its recognized importance, there is very little research on human judgment in technology-supported RM decision-making.

Several studies in the airline forecasting literature reveal that human judgement is valuable (Bach, 1999; Loew, 2000; Mukhopadhyay, Samaddar, & Colville, 2007; Weatherford, 2016; Zeni, 2003). Yet, judgmental adjustments have rarely been studied in the context of hotel revenue management forecasting. Kimes (1999) conducted a study on forecast data of approximately 90 hotels of a large North American hotel chain and concluded that more accurate group forecasts were achieved in larger hotels with a higher dependence on group business and with more frequent forecast updates in the month before arrival. However, these results were limited to group business and are therefore not representative of total hotel occupancy, which also includes transient business. In their analysis of 57 experienced revenue managers, Schwartz and Cohen (2004a) found that the nature of the user interface influenced the way revenue managers adjusted computer forecasts. In their subsequent study conducted on the same data, Schwartz and Cohen (2004b) demonstrated that subjective estimates of forecast uncertainty depend on an individual’s industry experience and gender. However, the generalizability of these studies is limited. Albeit hotel and airline revenue management share key characteristics, there are important conceptual differences such as that the length of stay of hotels has a network structure (i.e., the displacement effect), and that arrival demands for multi-night stays and the length of stay are stochastic (Chiang, Chen, & Xu, 2007; Lai & Ng, 2005). Also, these two hotel studies were conducted with a relatively small number of participants using an experimental design and on simulated data. Moreover, the studies pertained to a limited timeframe; four months and seven weeks of data respectively. Additionally, computing power has increased drastically in recent years,

enabling the utilization of more complex RM models and computer algorithms. Therefore, there is a need for research on the current role of human judgment in technology-supported RM decision-making.

Revenue management systems generally consist of multiple dynamically connected modules, where the forecasting module is seen as a starting point of the process and its output has a crucial impact on other modules (Ghalia & Wang, 2000; Talluri & Van Ryzin, 2004). Accurate forecasts are important and estimates suggest that a 20% reduction of forecast error could translate into a 1% increase in revenue generated from the RMS (Talluri & Van Ryzin, 2004).³ Most of the literature on forecasting in RM largely focuses on mathematical design and implementation of more accurate forecasting models, such as time-series forecasting methods and Bayesian forecasting methods (Talluri & Van Ryzin, 2004). Also, most research attention is given to the airline and tourism industries, thereby ignoring the unique features of hotel occupancy forecasting (e.g., pick-up forecasting, length of stay).

The academic empirical work on how the hotel RMS forecasts are used and modified by revenue managers is scarce in hospitality research literature. In the generic operations research literature, forecasting accuracy has been greatly improved by the use of automated forecasting support systems. However, Goodwin, Fildes, Lawrence, and Nikolopoulos (2007, p. 403) observe that “while modern commercial forecasting systems provide access to powerful statistical methods and the ability to link easily to large databases, their design has largely neglected the role that the judgment of users plays in the forecasting process.” This human interaction with the automated forecasting system typically happens when the forecasting module generates forecasts and before these forecasts are fed into the optimization module to generate proper recommendations. At this stage, most RMSs provide a possibility to override the forecasts. These overrides are also referred to in the literature as judgmental adjustments. The research findings on the value of human expertise, however, are contradictory. According to some studies, a combination of statistical forecasting with judgmental forecasting should lead to improved forecasting accuracy (Donihue, 1993; Fildes et al., 2009; McNees, 1990; D. S. Turner, 1990), whereas other work demonstrates that forecasters often make unnecessary adjustments (Goodwin & Wright, 1994; Lawrence, Goodwin, O’Connor, & Onkal, 2006; J. S. Lim & Oconnor, 1995). These conflicting findings indicate a need to understand deeper the role of judgment in the hotel forecasting context.

3 The forecasting module generates constrained and unconstrained demand forecasts. While there are other types of revenue management forecasts (e.g., strategic forecasts, revenue forecasts, and operational forecasts), demand forecasts are generally considered as key (Cullen, 2015, p. 47).

To summarize, hotel revenue managers increasingly rely on their RMSs, in which the forecasting module plays a crucial role as it influences all other modules and critical decisions, including optimization and pricing. Although human judgement is necessary for a successful forecasting process, only few empirical studies have been carried out to examine judgmental adjustments in a hotel RM forecasting context. Thus, a better understanding of the complex phenomenon of user-system interaction and its impact on forecasting accuracy is needed, as accurate forecasting is a cornerstone for hotel revenue management performance. In the next section, the aim and the objectives of the research are presented.

1.2 Aim and Objectives

To provide direction for the research, the following overall purpose statement is formulated:

The aim of this study is to improve our understanding of judgmental adjustments in hotel revenue management forecasting by exploring the impact of user overrides on the accuracy of system-generated hotel occupancy forecasts at multiple forecasting horizons.

The term *judgmental adjustments* refers to “revisions of statistically generated forecasts using relevant domain knowledge” (Lawrence et al., 2006, p. 500). These revisions include *user overrides* (i.e., manual adjustments of system-generated hotel occupancy forecasts).⁴ *Forecast accuracy* is defined as the degree to which the forecasted hotel occupancy conforms to the actual occupancy (Hyndman & Koehler, 2006). *Forecasting horizon* is defined as the length of time into the future for which the occupancy forecast is generated (Lawrence, Edmundson, & O’Connor, 1985). To achieve and clarify the research aim, three objectives are formulated:

- 1. To investigate the applicability of forecast accuracy measures to evaluate judgmental adjustments of system-generated hotel occupancy forecasts.
- 2. To examine the accuracy of non-adjusted and adjusted hotel occupancy forecasts in the context of multiple forecast horizons.
- 3. To examine the impact of different characteristics of judgmental adjustments on the accuracy of the system-generated forecasts.

4 The terms ‘judgmental adjustments’ and ‘user overrides’ will be used interchangeably throughout the dissertation, since this thesis does not investigate other judgmental adjustments except for user overrides.

In addition, two overarching research questions are formulated to guide the enquiry:

- 1. To what extent do judgmental adjustments of the system-generated occupancy forecasts impact forecasting accuracy?
- 2. How do different characteristics of judgmental adjustments impact on the accuracy of system-generated hotel occupancy forecasts?

Figure 1 illustrates the relationship between aim, objectives and research questions.⁵

1.3 Outline of the Methodology

This research employs a quantitative design utilizing a longitudinal perspective. A longitudinal study is considered appropriate as it makes it possible to observe how forecasting accuracy is affected by user interventions (i.e., judgmental adjustments) at multiple occasions over the forecasting horizon. In this way, the dynamic and iterative nature of the forecasting and re-forecasting processes can be captured, as well as the time-dependent and seasonal nature of demand, which typically differs per day, week, and month (Cetin, Demirciftci, & Bilgihan, 2016).

Three studies are executed to address the research objectives. Real-world hotel occupancy forecast data are collected which include key data such as system-generated demand forecasts, detailed data on judgmental adjustments, and actual hotel occupancies.

Study 1 comprises hotel daily occupancy forecasting data of 2,043 triples of (a) daily occupancy predictions by RMS, (b) daily manual forecast of revenue manager and (c) daily actual hotel occupancy data across multiple forecasting horizons for a mid-sized five-star hotel situated in the Netherlands, belonging to a large international hotel chain. The data include daily room night forecasts at six segment levels for a two-year period, from January 2011 to December 2012. Study 2 includes forecast data of, in total, 20,081,973 cases from 1,752 hotels for the occupancy period 24 March 2014 to 7 April 2017. Data are obtained from city, resort, airport, and casino hotels from seven geographical regions including Europe, North America, Asia, Middle East & Africa, Australasia, Central America, and South America. Study 3 data represent an extended subset of the Study 2 dataset and contain detailed forecasts and judgmental adjustments data only for those occupancy days for which one or more user overrides took place. Study 3 data consist of a total of 228,649 cases of judgmental forecast adjustments from 1,752 hotels worldwide, for the occupancy period 24 March 2014 to 7 April 2017.⁶

5 To narrow the study’s focus, sub-questions are developed; they are listed on the right side of Figure 1.

6 Full details on the data can be found in the sections 2.3.1., 3.3.1., and 4.3.1 of this thesis.

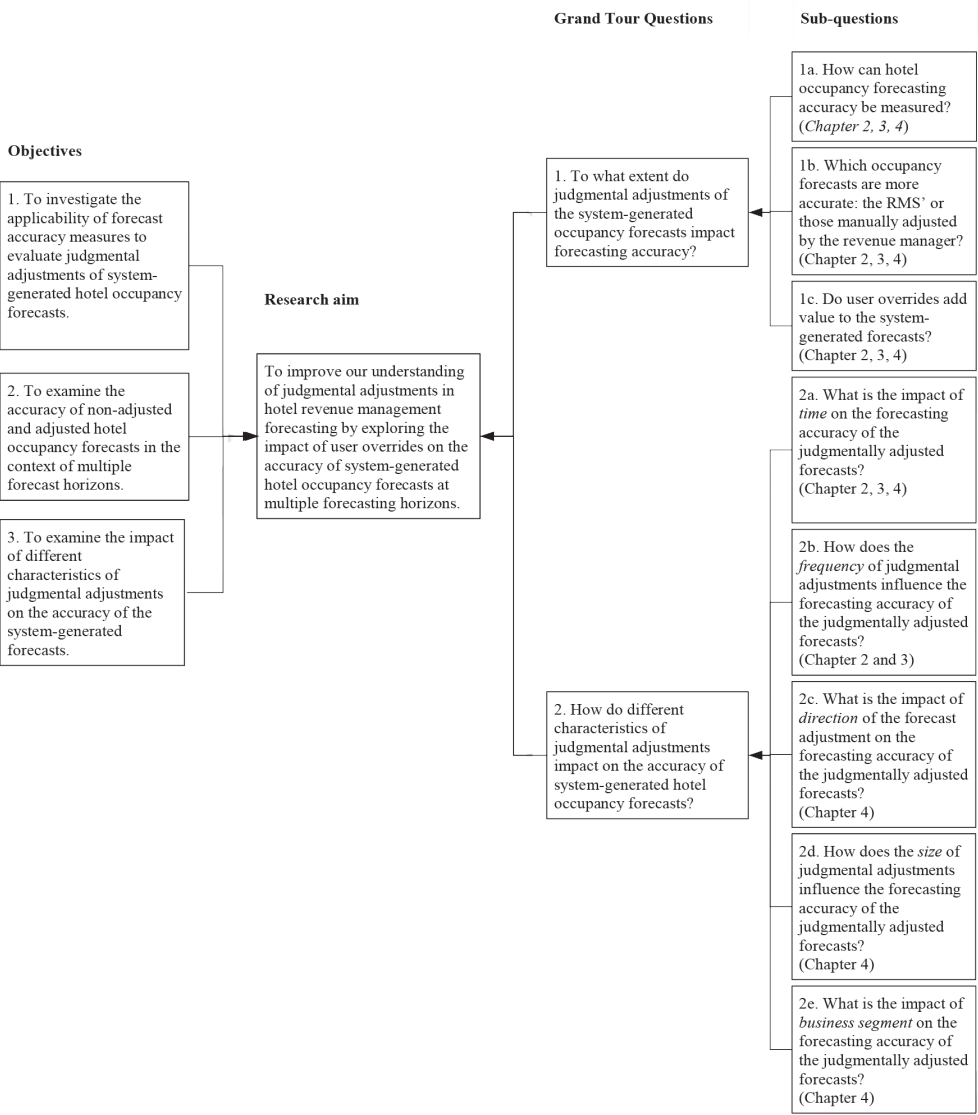


Figure 1: The relationship between aim, objectives, and research questions

The data are analyzed using the software package SPSS (version 23, release 23.0.0.3). The data analysis includes both a descriptive data analysis and a multilevel regression analysis. The multilevel analysis is chosen as the analytical approach since the data have a hierarchical or nested structure. This method is referred to in the literature under a number of names including hierarchical linear modeling (HLM), mixed linear modeling, or growth-curve modeling (Dedrick et al., 2009). The multilevel regression model can

be viewed as an extension of the classical multiple regression model as it adds the possibility to examine the relationships between variables measured at different level of the multilevel data structure. Multilevel analysis is considered appropriate as it overcomes an important limitation of conventional multiple regression analysis which relies heavily on the assumption of independence of observations; this is often violated with nested data (Hox, Moerbeek, & Schoot, 2018).

1.4 Delimitations

The main interest of this thesis is to gain an understanding of the impact of judgmental adjustments on the accuracy of system-generated hotel occupancy forecasts. While in the operations research literature the term judgmental adjustments tends to refer to the revisions of statistically generated forecasts using relevant expert domain knowledge (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Flores, Olson, & Wolfe, 1992; Lawrence et al., 2006), the term is sometimes equated to all types of judgmental inputs in forecasting. These inputs, however, are usually defined more broadly than judgmental adjustments, and according to Mathews and Diamantopoulos (1986), they include three distinct forms: *a priori incorporation*, *concurrent incorporation*, and *a posteriori incorporation*. However, it is beyond the scope of this study to examine all aspects where forecasters execute their judgment related to the selection, specification and modification of the forecasting model parameters or to the blending of judgmental and statistical forecasts through a combining algorithm. Although in the context of automated RMS there are various ways in which users may influence the system (e.g., adjusting prices, changing overbooking limits), the scope of this study is the judgmental adjustment of the occupancy forecast only. Hence, strategic, operational and revenue forecasts are out of scope for this study. Also, the thesis does not examine RMS interface design features and their impact on system users' adjustment behavior.

1.5 Practical Significance

Hotel performance is heavily affected by seasonality of demand (Vives, Jacob, & Payeras, 2018). Accurate forecasting is therefore a cornerstone for financial success and impacts decisions such as pricing and operational planning (Weatherford & Kimes, 2003). Whereas a computerized revenue management system (RMS) supports the forecasting process and is indispensable for hotel performance, an autonomous (i.e., human-independent) RMS is not yet feasible (Weatherford, 2016). Accordingly, revenue managers continuously interact with their RMS, and the resulting system-supported RM decisions are an integral part of hotels' daily practices. However, the impacts of this crucial human/RMS interaction are not sufficiently investigated in the practitioners' or academic literature.

This thesis provides an important opportunity to advance our understanding of a complex and dynamic process of hotel forecast generation and adjustment. Moreover, it offers initial insights into interactions between the Revenue Manager and revenue management system within the context of hotel forecasting. The findings can be applied by hotel Revenue Managers to facilitate their systematic and periodic evaluation of their judgmental adjustments, and in this way to help them identify adjustments that add value. This study has also been designed to provide insights on how different characteristics of judgmental adjustments impact forecasting accuracy, and ultimately, to assist hotels and RMS solution providers in their quest to improve the way judgmental adjustment to system forecasts are constructed and thereby to improve their profitability.

1.6 Structure of the Thesis

The overall structure of the research takes the form of five chapters, including this introductory chapter. Figure 2 illustrates the organization and structure of the thesis.

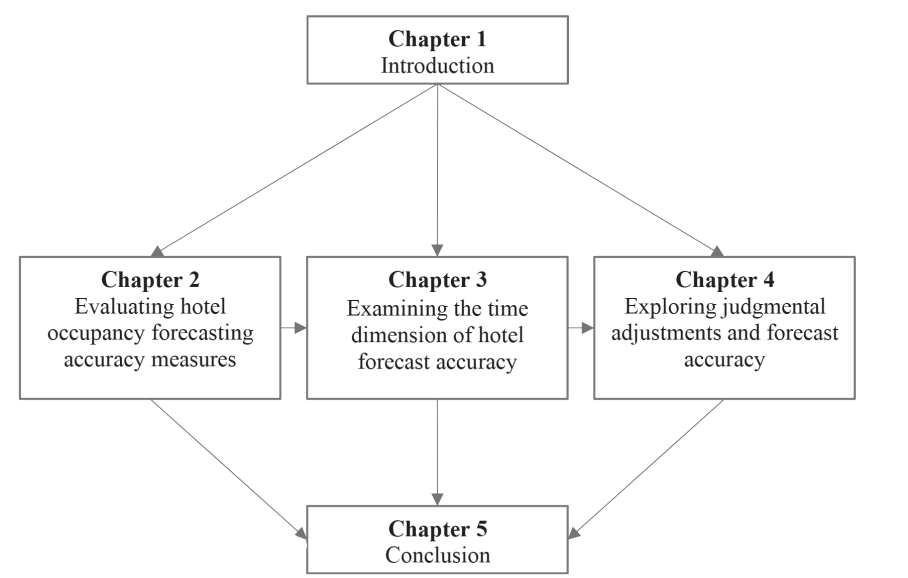


Figure 2: Structure of the thesis

Chapters 2, 3 and 4 provide the results of three empirical studies. Chapter 2 verifies the applicability of existing forecast accuracy measures for the evaluation of hotel forecasting performance. This chapter provides a critical review and discussion of forecasting accuracy measures and lays the foundation for how forecasting accuracy is measured in the subsequent two studies, also addressing

the aspects of level of data aggregation and multiple forecasting horizons. Since both hotels and customers make time-dependent decisions, Chapter 3 examines the critical relationship between forecasting horizon and forecasting accuracy for non-adjusted and adjusted hotel occupancy forecasts. It demonstrates empirically that forecast accuracy improves as the date of arrival nears and that the relationship between time and forecast accuracy is complex. Chapter 4 explores the impact of various characteristics of judgmental adjustments on improvement in forecasting accuracy, with regard to the forecasting horizon, the frequency, direction and size of adjustments, and the type of business segment. It finds that early forecast improvements are associated with lower improvements in accuracy, the judgmental adjustments to the group business are associated with larger improvements than adjustments to transient business and that the size of judgmental adjustments is positively associated with improvement in accuracy. Chapter 5 draws on the findings of the three chapters, tying up the theoretical and empirical strands, and discusses this thesis’s contribution to knowledge, its implications for practice, and directions for future research.