The Booking Window Evolution and its Impact on Hotel Revenue Management Forecasting

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ABSTRACT

Travel booking behavior has changed substantially over the past two decades. The emergence of new technology and online intermediaries has provided travelers with the flexibility to book up until the date of stay. This has created a fast-paced, dynamic booking environment that disrupts traditional revenue management strategies focused on pricing and allocating rooms based on the time of purchase. The study explores the joint effects of technology and the economy on booking window lead times. It also evaluates a range of forecasting techniques and the importance of utilizing the booking curve for forecasting in dynamic booking environments.

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Table of Contents

List of Figures

List of Tables

Introduction

The emergence of revenue management (RM) over the last 30 years has created substantial benefits for the hospitality industry in pricing and rate optimization. Revenue management can be implemented in industries that have perishable products such as hotels and airlines (Schwartz, 1998). These industries experience a constrained capacity to be sold for a given duration (ex. flight or hotel night) and are unable to accumulate inventory to be sold at a later date. Using revenue management optimization algorithms, revenue managers can improve the profitability of hospitality companies by allocating their inventory to the customers with the highest willingness to pay. This process is typically conducted by forecasting demand, then opening and closing rate levels based on the demand and the probability of selling a product (Phillips, 2005). Utilizing this process, the hotel, airline and rental car companies are able to generate more revenue by efficiently allocating their perishable inventory. The success of RM can be seen across these industries with revenues increasing from $200-$500 million for airline companies with revenues over $1 billion (Relihan, 1989). Similarly, hotel companies have increased revenues from 2-5% from utilizing revenue management systems (Choi & Kimes, 2002).

Since its inception in the 1980's, revenues have continued to improve as the sophistication of the revenue management systems continues to evolve. Along with its success, new challenges have emerged with the influence of technology. Prior to 2000, booking reservations was largely dependent on information available from travel agents who had access to global distribution systems (GDS). During this time, when a reservation was made to a travel agent, the agent would enter the booking information into the GDS which would communicate through a switch to a travel company's central reservation system (CRS) (Choi & Kimes, 2002; O'Connor & Frew, 2002; Thakran & Verma, 2013). This information would then be communicated to the property management system where inventory levels would be updated. At the time, the process was relatively efficient. Travel agents bridged a key information gap regarding what travel products were available and at what cost, instead of forcing the customer to physically call various locations.

Given this structure, revenue management systems capitalized on a segmentation scheme centered around the time of purchase. This was largely attributed to leisure travelers booking well in advance due to the lack of information available, while business travelers booked close to the date of travel due to the nature of business. For years, revenue management systems leveraged price discrimination strategies by adjusting rates upwards as the date of stay neared, considering that business travelers had a higher willingness to pay. These adjustments in rate levels largely provided the revenue increases for travel companies by selling the greatest amount of perishable inventory at the most optimal price.

The recent changes in booking behavior due to technology have presented new challenges for revenue management practices. It is now more difficult to predict who is booking when and at what price, fundamentally changing the traditional segmentation scheme. The study first investigates the causes of recent booking window shifts to identify the drivers that have influenced change. In later chapters, revenue management forecasting algorithms are compared to identify the most accurate models amidst dynamic booking windows. Finally, these techniques are grouped into subclasses to further identify which data types are most important for forecasting in dynamic booking environments.

Literature Review

The Evolution of Technology and Travel Purchases

The emergence of the information age and an internet driven society changed the way travel products were booked with online travel agents (OTAs). The first large scale OTA was Expedia, developed by Microsoft in 1996, followed by Priceline in 1997 (Barthel & Perret, 2015). These outlets began selling holiday reservations online, but quickly expanded to include all aspects of hospitality, incorporating everything from flights and hotels to cruises and restaurants. Soon thereafter, several other sites emerged such as Orbitz in June of 2001 and Kayak in 2004 (Empson, 2012; Thomas, 2016). The success of these distribution channels is attributed to the fact that they provided customers with a new and much improved resource for evaluating travel decisions. The effects can be characterized in two distinct ways (O'Connor & Frew, 2002), the first is that reservation information was now available in a timely and up to date manner in which, a traveler could evaluate several different options at any time. Secondly, the actual purchase could be conducted online. Although these changes seem relatively simplistic, there impacts have changed the distribution of hospitality services forever. Reservations could now be made on the go and the information regarding where to stay, when, and at what price was not dependent on communicating with a travel agent or property. The momentum for the new booking process has sustained as the uncertainty associated with travel decisions is reduced. The distribution channels have assisted travelers in minimizing the information gap between expectations and what a customer may actually experience with reviews and recommendations.

This shift in consumer behavior has generated significant discussion within the travel industry due to its shear dominance. For example, consider that in 2013, 45% of all European travel revenue was conducted on OTA's (Barthel & Perret, 2015). In the first quarter of 2015, bookings through OTA's increased 15% year over year, while reservations made through hotel websites increased 7.1% (Mahmoud, 2015). Similarly, over the same period, bookings made directly to the property (face-face or by phone) dropped 8.4% and bookings through call centers dropped 6.1% (Mahmoud, 2015). In a recent study conducted by Compete and funded by Expedia Media Solutions, it was reported that customers visit travel sites approximately 38 times during the 45 days leading up to a booking (Worgull, 2013). Even more revealing is that travelers visited OTA sites 8 times during the week leading up to booking, with 1/3 of these visits occurring on the day of (Worgull, 2013). The trends suggest that online booking will only continue to grow, with OTA's serving as one of the dominant resources for travelers. The online booking environment is also technologically dynamic with the recent emergence of mobile bookings from smart phones or tablets (Thakran & Verma, 2013). In 2014, 25% of leisure travelers booked with a smart phone up from 15% in the prior year (Gasdia, 2015).

The shift in booking behavior has led researchers to begin considering the implications for revenue management. The traditional purchase process is composed of 5 unique steps known as need arousal, information search, evaluation, purchase decision and post-purchase feelings. However, for hospitality products, purchase and consumption typically occur at different time periods. In addition, two components of the purchase phase, price and availability are not stable over the purchase cycle (Schwartz, 2006). Ultimately these factors can influence a customers' willingness to pay and decision of when to purchase.

To understand the decision process, Schwartz (2000) highlights the four options a consumer can make when purchasing a hotel room, these include Book, Book and Search, Search, and Other (select another product). The study by Schwartz (2006) describes the interaction of these decisions with regards to price and utility, which dictates the decision of the customer. These relationships create decision zones that are derived by maximizing a customer's utility with regards to the price, willingness to pay and customer perceptions (Schwartz, 2006). The ultimate goal for researchers and industry professionals is to develop strategies that influence the outlined factors to move the zone switching points (Example: Book to Book and Search) in the decision process to higher rate levels (Schwartz, 2006). Some of these strategies include increasing the perception of a sellout or decreasing the perception of a discount, both of which can increase the book and book and search zone switching price points and capture more bookings.

Further complicating the purchase process is the effects of time on these decision zones. Customer expectations and subjective assessments of future dates cannot be assumed to be stationary as the date of stay gets closer (Schwartz, 2008). For instance, as time progresses the number of searches a customer can conduct diminishes; similarly, the perceptions regarding the chance of a sell out or price change are not static. It has been shown that time dependency can impact the booking decision even if the rate does not change (Schwartz, 2008). These findings highlight the effect that time dependency can have on booking decisions, and further stresses the complex predicament of the advanced purchasing process, which plays an integral role in decision making of revenue managers and revenue management systems.

The Deal Seeking Culture & Time of Purchase

It is evident that the traditional purchase process that was limited in the past has now evolved into a dynamic environment that has serious implications for revenue management with regards to when a purchase is made. The emergence of the internet provides several new factors (price changes, sell out risk etc.) that may influence the purchase decision. Given the dynamic nature, travelers may continuously evaluate these factors as they may change up until the actual date of stay. As the internet has become more prevalent, it has created consumer search behaviors that involve adaptive search patterns, learning elements and expectations updating (Schwartz, 2008; Worgull, 2013). Coinciding with the change in when travelers choose to book, is the price that customers are willing to pay. What has arisen due to the internet has largely been considered a "deal seeking environment". The reasons for development of this deal seeking culture are outlined by O'Connor (2002). He states three key underpinnings, the first is that internet retailers (such as Amazon) compete with traditional outlets largely based on price. Secondly, consumers are aware of the lower distribution costs online, from eliminating the middle man. Finally, last minute promotions pushed by hospitality companies are used to sell distressed inventory, which has generated traveler associations with cheaper prices (O'Connor, 2002; Decko, 2004). Further adding to the feasibility of the deal seeking environment is the decrease in search costs which has made price shopping easier (Jang, 2005; Sahay, 2007). Finally, the deal seeking culture was confirmed by Yesawich et al. (2000) in their survey "2000 National Leisure and Travel Monitor" in which it was reported that almost 6 in 10 travelers search for the "lowest possible rates".

A more scientific argument for the development of the deal seeking culture has been presented by Schwartz & Chen (2012). They argue that the purchase decision is fueled by both utilitarian and hedonic motivations. In the traditional booking structure, once a consumer decides to take a trip, the utilitarian motivations describing the need to book the reservation dominates the purchase decision. A traveler selects a destination and then selects a product that derives the highest benefit (utility) from the booking. However, with the emergence of online information, hedonic motivations may enter the purchase decision. In this instance, travelers know that prices and availability change over time. The ease of checking rates creates a purchase process that travelers enjoy. Ultimately, these customers generate additional utility from deal seeking in the online environment in hopes of finding a cheaper rate. The investigated relationships show that the impacts of revenue management strategies, such as sell outs or paying a higher rate, must have a large enough impact on the purchaser to generate a booking closer to the traditional booking time. If the perceived risk is not high enough, consumers will continue to search for a better deal to obtain the enjoyment from the possibility of finding a cheaper rate.

Overall, the emergence of these online intermediaries has created significant benefits for the traveling consumer through its reduction in the information gap and ability to make travel decisions, however, it has also had substantial implications for revenue management. The first is with regards to the deal seeking culture in that travel products such as hotels may be viewed as a commodity rather than a brand or specialized product (Carroll & Siguaw, 2003). This makes pricing particularly more difficult as differentiation may not be a way to maximize revenues. The second is that the decrease in search costs and deal seeking culture has shifted the booking window (Dacko, 2004; Mayock, 2011; Lee, 2013). In other words, the availability of travel prices and information has altered when consumers book, detrimentally impacting the traditional revenue management structure and segmentation scheme (Schwartz, 2006). Recall that prior to OTA's and internet bookings, leisure travelers tended to book well in advance, while in today's internet economy these travelers have the flexibility to book up until the date of stay. This has generated significant problems since the accumulation of bookings occur in a different fashion than they have historically and provide less information for revenue managers and algorithms to operate efficiently. Decisions such as when to open or close rate levels, or which pricing levers to pull is inherently more difficult as inventory may be categorized as distressed earlier. These price changes ultimately influence the customers' willingness to book (Chen & Schwartz, 2008).

To highlight the relationship between time of purchase and deal seeking, experimental research has shown that the propensity to book increased as the date of stay drew near, however lower expected future rates decreased the probability of booking. Therefore, although consumers have a higher need to book as the date of stay nears, they are also likely to wait if they perceive the rates to be lower (Chen & Schwartz, 2013). These results support the hedonic motivations suggested by Schwartz and Chen (2012) and this effect has also been investigated by Toh et al. (2011). In his study, 13 properties were tracked daily for quoted rates on the hotels website, Expedia and Orbitz. The results of the study show that the quoted rate in the first 14 weeks of the booking window were higher than the rate quoted during the last 3 weeks of the window. The authors suggest this could be due to the shortened booking window. In the study, an interview with a hotel employee stated that "It used to be a couple weeks when (late-booking customers) rushed in. Now it's three days. We're not sure if it's due to the recession the internet or both." Further evidence of the "deal seeking" culture and shrunken booking window is discussed by Granados et al (2012) who show that consumer demand for airline tickets is more elastic via online channels than offline channels. This is largely attributed to the fact that leisure travelers are more likely to use these channels and are more price sensitive (Granados et al, 2012).

Economic Indicators and Travel Purchases

Although the internet has provided travelers with the ability to book later and search for deals, it does not guarantee that all of these travelers are deal seekers or choose to wait. Several external factors may have conflicting impacts on the booking process. As the quote from Toh (2011) indicates, the economic situation plays a pivotal role in when consumers book and is also likely to affect the price and duration of stay (Legre, 2004; Toh, 2011). This is because travel and tourism is largely considered a luxury product (Crouch, 1994; Smeral 2009). In other words, customers will forgo vacations for necessary products such as food and clothing. Therefore, purchases of these products tend to vary based on the state of the economic climate, with high responses to changes in income, unemployment levels, and relative prices of goods, among others (Legre, 2004; Smeral, 1988; Smeral, 2009). When looking at income levels specifically Legre (2004) reports that the propensity to travel increases as income levels increase. However, the effects of income elasticity on travel for lower income individuals is far greater than for those with higher incomes (Legre, 2004). These findings suggest that economic factors such as income and unemployment can have substantial effects on travel, influencing when a consumer books as well as at what price and duration.

How each of these factors influences occupancy rates is discussed by Choi (2003). In the study, an auto correlation function is used to create cross correlogram plots between economic indicators and gross hotel commerce. Although several indicators were identified, notable leading indicators of hotel revenues were CPI for motor fuels (lag -4), GDP of Service (lag -2) and the hotel stock index (lag -2). Coincident indicators of note included GDP, hotel occupancy percentage, consumer confidence, and consumer expenditures in the service industry. Finally, lagging indicators include GNP (lag 1), total employment (lag 1) and the unemployment rate (lag 2). These factors were used to build composite indices to forecast hotel commerce and may be useful in determining not only how much may be spent on travel but also when bookings occur.

Overall, the relationships between economic indicators and the travel industry are well documented, it is important to note that not all properties are impacted the same. Ismail et al. (2002) show that a hotels segment and location respond differently to changes in the market. Their results show that high priced segments were most volatile while low priced segments were least volatile in terms of RevPAR and the market. From a location perspective, urban properties have a strong response to market changes while airports and highway hotels were least affected (Ismail et al, 2002). These results are largely attributed to the theory of trade up and trade down effects. Travelers tend to trade up (to higher segments) when the economy is good but trade down to lower priced options when the economy is bad (Ismail et al., 2002; Jones, 2005). The volatility of high priced segments is because there isn't any trade down gain because they are the top segment. Similarly, mid-priced segments may add trade down customers from luxury segments when the economy is bad. These findings support the fact that business travelers and high income travelers are least effected by the economy while lower income leisure travelers are most impacted.

Travel Purchases Taken Together

Ultimately, there are several compounding factors that influence travel booking decisions today. In one domain, there are the impacts of technology which has provided increased flexibility in the way consumers book, when they book and at what price. In the second domain are the economic effects that are impacting the ability of consumers to take a trip and similarly impacting when they book and at what price and duration. Over the past few years, reports have shown conflicting arguments with regards to the shift in the booking window. At times reports have suggested the booking window was shrinking as Omni hotels reported that the average lead times for large meetings dropped by 200 days between 2009 and 2011 (Mayock, 2011). A report from Travel Click (2012) reviewed reservations data for 25 North American markets from August 2012 – July 2013. Their report showed committed occupancy (advanced reservations) was up 3.5% for group travelers and 4.4% for leisure travelers, with an overall ADR increase of 4.1% (Travel Click 2012). In a similar report, Manley (2016) cites that Travelclick transient bookings were down -1.9% while average daily rate is up 2.1% (Manley, 2016). Interestingly, group bookings were both up in committed occupancy and ADR over the same period (April 2016-March 2017). In another article, Denihan Hospitality EVP Tom Botts stated that the average booking was conducted 39 days in advance up from 35 the previous year (Worgull, 2013). These reports suggest that the recent lengthening of the booking window is due to an improved economy (Worgull, 2013). As Tim Hart, the Executive Vice President for Research and Development at Travel Click states "Business and leisure travelers are booking further in advance, no longer holding out until the last minute (Travel Click 2012)."

The impact of the internet on revenue management cannot be understated as its' potential impacts on forecasting, pricing and booking limits are critical to optimization algorithms. It also seems evident that the change in booking behavior falls particularly on the leisure travel segment as business travelers are likely to be booking within the same window while leisure travelers have the ability to book at their own discretion. The evolving dynamic of technology and purchasing power within the economy further complicates the accuracy of the forecasting process. Forecasts within the hotel industry are typically conducted for several factors including occupancy by rate class, length of stay, walk-ins and no shows, among others. The more accurate the forecasts that feed the revenue management systems, the better revenue managers and systems can make decisions. This highlights the need for research to be continually conducted to enhance the forecasting tool kit, attempt to discover the most accurate methods and to find methods that are best suited and adaptive to these dynamic booking environments.

Forecasting in Revenue Management

To produce forecasts, the data readily available to a hotel property includes historical booking information, current booking information and additional information (Schwartz et al, 2016). The historical data is comprised of bookings that have occurred on similar days in the past. This includes booking information for the same day year over year. The current booking data is comprised of the reservations on hand for a date of stay in the future, while additional information contains outlier days not typically observed. These three types of information are then used to produce a forecast by leveraging a variety of techniques that fall under one of three subclasses (Weatherford & Kimes, 2003). The first subclass utilizes the historical data and involves a time series approach. The inclination behind this approach is that past observations will likely repeat due to the seasonality involved with travel. The second subclass is with regards to the current data. As bookings accumulate for a particular date of stay, the goal is to extrapolate the current bookings on hand to determine how many additional rooms or reservations will be picked up. The final subclass includes the current industry standard of combining the historical and current data models together to produce a final forecast (Weatherford & Kimes, 2003). When the date of stay is far in advance (greater than 90 days) the historical information tends to receive a higher weight as reservations have yet to accumulate. However, as the date of stay approaches, bookings begin to occur more frequently and the current data technique begins to receive more weight. This is where the ability to yield rate levels becomes strategically important in the optimization algorithms as booking limits are opened and closed based on the bookings and forecasted demand (Chen & Kachani 2007; Phillips, 2005).

Several studies have attempted to determine which forecasting techniques are the most accurate and robust for forecasting in revenue management. The first major study conducted by Weatherford and Kimes (2003) tested seven different models on a variety of hotels to predict room nights, as well as forecasts by rate class and length of stay. The historical models tested included exponential smoothing, moving average and Holt-Winters double exponential smoothing. The current data models included linear regression, log-linear regression, additive pick-up and multiplicative pick-up. The study tested these models on two separate data sets from hotel properties owned by Choice Hotels and Marriot. Results of their study show that exponential smoothing was the most accurate using MAE, while additive pickup was the most accurate using MAPE (Weatherford & Kimes, 2003). The worst performing methods were log linear and multiplicative pick-up methods. In a similar study conducted by Chen and Kachani

(2007) the exponential smoothing, classical pick-up, advanced pick-up, linear regression and vector autoregressive (VAR) methods were tested with a variety of estimation and hold out sample sizes. Their results show that regression was the worst method while a combined version of the exponential smoothing and advanced pick-up performed well (Chen & Kachani, 2007).

Researchers have also tested several novel ideas outside of the traditional time series and extrapolation methods to improve accuracy, particularly in the face of the dynamic booking windows. To account for when consumers are booking, researchers have attempted to add consumer pulse data to traditional time series models (Pan et al 2012; Yang et al 2013). These methods include visits to travel websites and travel search queries as additional explanatory variables in ARIMAX models. Their results show that consumer data regarding travel planning can significantly improve the accuracy of forecasts using the ARIMAX model over the traditional ARIMA model (Pan et al 2012; Yang et al 2013). Researchers have also begun to add additional information to the forecasting models to improve accuracy within markets. Schwartz et al. (2016) suggest using a combination of several properties forecasts to determine an optimal forecast. In this instance, each property makes a forecast and would then share that forecast with others in the properties competitive set. The benefits lie in the fact that each property has different information, market knowledge and modeling techniques that could be advantageous to the others. These properties then use weighted combinations of the competitive set to obtain a more optimal forecast. The results show that the combination improves forecasting accuracy for hotels that have poor forecasts on their own or have occupancy rates that are highly correlated within the market (Schwartz et al. 2016).

Forecasting in the Dynamic Booking Environment

The challenge surrounding forecasting with dynamic booking windows is most evident with regards to current data forecasting techniques. Traditional pick-up methods that are not frequently updated due to changes in consumer behavior may be problematic considering that reservation pickup rates may change over time (Webb, 2016). As Tim Hart, Executive Vice President, Research and Development at TravelClick stated in a recent news article “Business and leisure travelers are booking further in advance, no longer holding out until the last minute. For hoteliers, this means that it is important to account for this shift in the booking window in their forecasting, relying less on comparisons to last year’s booking pace and more on recent booking pace trends.” If technology or the economy “shrinks” the booking window, adding the historical average pickup may not be an accurate approach and inventory may be categorized as distressed earlier; similarly, the reverse is also practical.

Interestingly, the study by Tse and Poon (2015) reveal that hotel industry professionals tend to focus on future pickups from a fixed point in time, ignoring how reservations accumulate. In their article, industry professionals state that “pickup rates at different times are different and thus the booking data in early days or weeks bear no relevance in forecasting.” This argument is particularly problematic in the face of dynamic booking windows as the shift in reservation lead time can greatly alter the pickups forecasted for future room nights. Tse and Poon (2015) correctly indicate that forecasting techniques leveraging only future reservation pickups are utilizing an approach that exhibits the Markov property in mathematics. The Markov property indicates that future behavior of a process is not altered by the additional information of past behavior (Lee 1990, Tse and Poon, 2015). For forecasting in revenue management, this would imply that future bookings are independent from the current bookings on hand and how these reservations accumulate.

Forecasting in dynamic booking environments requires an understanding of what is dictating changes in the booking window and how to identify when these changes are occurring. Tse and Poon (2015) argue that the lead time for reservations will vary from period to period depending on several macro and micro factors (Tse and Poon, 2015). Specifically, macro factors related to the economy (unemployment, exchange rates, GDP) may impact booking behavior, while micro factors such as advertising and price promotions may also impact pickup rates. Therefore, Tse and Poon (2015) state that bookings on hand are a good indicator and reflection of all macro and micro factors that affect room occupancy and may carry through the entire booking period. This argument would suggest that the accumulation of the booking curve is critical to forecasting in dynamic booking windows.

Models have been investigated that may improve accuracy within these conditions. Schwartz and Hiemstra (1997) attempted to improve booking curve extrapolation by proposing a booking curves similarity match technique. In their study, they compare current booking curves (incomplete information) to past complete booking curves to identify dates of stay with similar pick-up. This method uses a distances metric every 10 days to compare similarities between curves. Once the similar curves are identified, they are combined to estimate the final number of bookings. This technique outperformed the competing techniques (autoregressive and higher order polynomials) with an average reduction in MAPE of 5.2% (Schwartz & Hiemstra, 1997).

In another approach, Tse and Poon (2015) tested the effectiveness of fitting a variety of polynomials to the booking curves at varying horizons. As the horizon moves from one month out to two weeks out, the method becomes increasingly accurate and demonstrates the potential success of using a second order polynomial on the booking curve rather than simple linear regression. Specifically, their study shows that trends and patterns in the data due to changes in booking lead times can be very useful for forecasting.

Ultimately, both authors argue that the accumulation of reservations is an important attribute for the extrapolation that should be leveraged. Other techniques of extrapolation, such as additive pick-up assume that previous reservation pick-ups are independent of future reservations. Both methods may help combat the dynamic booking patterns as the booking curves technique may map to previous booking curves under similar conditions (economic, technological, or other causes), while the higher order polynomial regression also accounts for how reservations accumulate.

New Forecasting Methods

As technology and computational power has improved over recent years, the techniques for forecasting have been refined and advanced. The most notable of these has been the emergence of neural networks. Neural networks have been used heavily in forecasting, classification and pattern recognition problems (Garson, 2014; Vellido et al.

1999; Weatherford, 2003). The technique was inspired by neuroscience to imitate a process that is like the human brain (Guthikonda, 2005; Zhang et al. 1998). Within the brain, neurons are connected and pass signals back and forth to communicate information for reaction. Generally speaking, a neural network attempts to imitate this process by creating linkages between inputs (predictors) and outputs (forecasts) (Garson, 2014; Hyndman, 2014). In a typical structure input vectors (variables) are introduced to the network. These inputs are connected by arc weights to hidden or output layers (Garson, 2014; Zhang, 1998;). The models are data driven techniques that learn from examples and can capture subtle or unknown relationships between the input and output variables (Zhang, 1998). The models also provide several advantages over traditional techniques in that they are self-adaptive, non-parametric and require few a priori assumptions (Garson, 2014; Zhang, 1998). In addition, they can capture any functional form and incorporate nonlinear relationships which provides significant advantages over traditional time series models (linear processes) (Vellido et al., 1999; Zhang et al., 1998).

Although several benefits of neural networks exist, there are also a few drawbacks. The first is that it is difficult to establish casual relationships between inputs and outputs (Garson, 2014). This is largely due to the structure of the network as the relationship of the predictor variables to the dependent variable is obscured by the indirect and iterative nature of the algorithms (Garson, 2014). Depending on the number of layers within a network, several weights and intermediate relationships may exist which make causal inferences difficult. Instead, the networks are best suited for processes that require high predictive power without justification as to which variable is deriving the solution. A second drawback is the issue of over-fitting as data driven methods can be unstable across samples so it is important to cross validate. This process requires one data set to fit the model and another to test for stability (Garson, 2014). It is also important to note that the process is largely data driven and somewhat random so several training iterations is recommended (Hyndman, 2014). Overall, the use of neural networks for research problems has gained increased recognition over recent years due to the flexibility the models provide. The models are particularly useful for forecasting where accuracy is of upmost importance in comparison to casual influence regarding which variables are included.

Multi-Layer Perceptron Models

Several neural networks have been derived to solve a variety of problems. One of the most common neural networks is the multi-layer perceptron model which is typically used for forecasting. This model is a feed-forward neural network where inputs are introduced to the model and pass information to hidden layers. The hidden layer communicates information forward to future layers until the output layer is reached (Correa et al. 2012, Garson, 2014; Hyndman, 2014). In the estimation process the back-propagation technique is used in which the error in the output layer is fed back to earlier layers to update nodes and optimize a prediction (Correa et al. 2012; Garson, 2014); this process is conducted after each iteration and is a gradient steepest descent method. The typical estimation process is supervised, which means inputs and outputs are known in advance and several iterations of training are used to estimate the model. The estimation process continues until the error is minimized or reaches a predetermined constant. The iterations are conducted several times to reduce randomness and the network weights are averaged together after all the iterations. The estimated model is then tested on hold out samples to ensure accuracy and reliability.

The extent of MLP applications is vast and has been leveraged by both researchers and practitioners in many fields. Within the business domain, these models have been used in the areas of accounting, finance and marketing (Vellido, 1999). From the hospitality and tourism perspective, the techniques have gained some popularity in recent years, particularly in forecasting for tourism, finance and revenue management. Uysal and Roubi (1999) use a multi-layer perceptron model to forecast Canadian tourism expenditures in the U.S. (Uysal et al. 1999). In another application, MLP's were used to predict occupancy rates for the Hong Kong hotel industry, as well as Japanese visitors to Hong Kong (Law, 1998; Law, 1999). All three papers show the ability of neural networks to outperform multivariate regression models and cite that this is likely due to unobserved relationships between the variables. The MLP techniques have also been used to forecast bankruptcy of hotel and restaurant firms with mixed success over the traditional logistic regression techniques (Kim, 2011; Park et al. 2012; Youn et al. 2010a. Youn et al. 2010b.).

Within the revenue management domain, researchers have utilized multi-layer perceptron models to predict demand for airline products. Weatherford et al. (2003) constructed a single layer feed forward neural network to predict the number of reservations for airline flights. The single layer neural network is the most basic architecture and his results show that the network was more accurate than traditional smoothing and regression techniques (Weatherford, 2003). In addition to performance, the error measures had more consistency between the estimation and hold out samples. This result coupled with the idea that only the most basic structure was utilized would suggest that further improvement could be obtained and may provide a superior method for this type of forecasting. In the revenue management transportation field, Tasi et al (2009) used a variety of neural networks to predict railway passenger demand (Tasi et al. 2009). Research suggests that like other disciplines the MLP technique has begun to gain further popularity for forecasting in the field of hospitality and tourism, and has shown potential within the field of revenue management.

Research Question 1

The reviewed literature and anecdotal observations suggest that the booking window is fluctuating over time. However, academic research has lacked in determining how technological changes in the booking process and the economic consumption climate have jointly impacted booking behaviors, particularly over an extended period of time. It may be that in general, technology has shrunk the booking window with brief swings up and down due to the economy. Similarly, the change in technology may have allowed consumers to book earlier but they were only doing so due to the economic crisis in recent years. Understanding where the shifts in booking lead times are derived is critical for revenue management operations as forecasting and prices are largely adjusted based on the accumulation of reservations.

Research Question 1: To what effect has technological change and changes in the economy had on booking window lead times?

Research Question 2

The fluctuation in booking window patterns presents significant implications for forecasting in revenue management. As the booking window changes, it is important to realize that it causes changes in the underlying data structure due to when reservations are observed. These changes inherently impact the accuracy of techniques and are likely to diminish the efficiency of forecasting methods if model parameters aren't updated accordingly. This is particularly true in current data techniques which are dependent on reservation pickups at various points in time (Webb, 2016). The issue can have detrimental impacts on revenues considering the key decisions such as what rate levels to open and close or what distribution channels to use are based on these forecasts. Lee (1990) has determined that a 10 percent improvement in forecasting accuracy can contribute up to a 3% improvement in revenues for the airline industry (Lee, 1990). Similarly, other studies have cited estimates that a 20% reduction in forecast error could increase revenues by 1% (cited in Koupriouchina et al, 2014). These results suggest the importance for continued research for forecasting within revenue management, particularly in the face of dynamic booking windows. Neural networks may provide increased forecast accuracy within hotel revenue management over an extended period; with data sets that contain shifts in the booking window.

Research Question 2: Can neural networks provide more accurate forecasts than traditional techniques, particularly with data containing booking window fluctuations?

Research Question 3

As the booking windows fluctuates, the accuracy of a current data techniques is likely to diminish. Previous investigations tend to be limited in their analysis regarding the robustness of techniques over time, when considering that these studies tend to utilize less than two years of data. These smaller samples are unlikely to exhibit significant shifts in reservation lead time and may be unsuitable to identify appropriate techniques to be used for an extended period. Specifically, it is important to understand if utilizing the accumulation of reservations in the forecasting algorithm provides a more robust model than techniques that ignore this information in the face of dynamic booking windows.

Research Question 3: Do forecasting techniques that utilize the accumulation of reservations in model estimation prove to be more robust as the booking window fluctuates?

Research Question 1

Methodology

To assess the impacts of technology and the economy on booking window fluctuations, the variables are first entered into an autocorrelation function (ACF) to assess their relationship with the booking window observations. The ACF reveals lagging or leading relationships between the independent and dependent variables and is similar to Choi (2003). The strongest identified relationships will be utilized to model booking window fluctuations. Sequentially, multivariate regression is used to measure the effects of the economy and technology on booking window fluctuations. The dependent variable is defined as the quarterly average booking window lead time, while the independent variables are the quarterly economic and technological lead or lag variables identified in the ACF. To account for differences in booking windows during different time periods and across properties, indicator variables were assigned for each location (P1-P14, p15 as reference) and quarter of year (Q1-Q3, Q4 as reference).

Formally

$$y(Booking\ Window)_t = a + b * (Economic\ Indicator)_t + c * (Technological\ Indicator)_t + P1 + P2 + P3 + P4 + P5 + P6 + P7 + P8 + P9 + P10 + P11 + P12 + P13 + P14 + Q1 + Q2 + Q3$$

Data

Booking window fluctuations are most likely due to changes in the booking behavior of the leisure segment who have more flexibility in travel plans. For this reason, data was obtained from 15 properties located in and around National Parks in the United States. These properties include locations around the entire continental US including the Northeast, Mid-Atlantic, Northwest, Midwest and Southwest regions. The average lead time for room nights at each property were obtained by quarter with the earliest and latest time periods recorded in Table 1. The range of the quarterly average booking windows are also provided for the given time periods.

Table 1. - Average Quarterly Booking Window

Property	Region	Earliest Quarter	Latest Quarter	Minimum QTR BW	Maximum QTR BW	Average QTR BW
1	West Coast	Q2 2013	Q3 2016	97	185	167
2	Mid Atlantic	Q3 2013	Q4 2016	32	97	48
3	North West	Q1 2014	Q4 2016	23	52	80
4	North East	Q1 2011	Q4 2016	18	67	44
5	West Coast	Q1 2014	Q4 2016	15	103	67
6	North West	Q1 2013	Q4 2016	31	77	52
7	North West	Q1 2013	Q3 2015	20	65	45
8	North West	Q1 2013	Q4 2016	20	117	57

9	Mid Atlantic	Q3 2013	Q4 2016	13	45	29
10	North East	Q1 2014	Q4 2016	21	69	51
11	Mid Atlantic	Q3 2013	Q4 2016	18	71	44
12	West Coast	Q1 2011	Q4 2016	26	94	65
13	Mid-West	Q1 2009	Q4 2016	21	67	43
14	West Coast	Q1 2011	Q4 2016	22	137	78
15	North West	Q2 2013	Q3 2016	32	93	70

To estimate the impact of technology, the number of reservations made online were taken as a percentage of total reservations. Specifically, all reservations made through internet channels (property website, OTA's) were taken as a percentage of all reservations for the given quarter of stay. The economic variables were downloaded from the United States Bureau of Labor Statistics and the United States Bureau of Economic Analysis. From the Bureau of Labor Statistics, the Consumer Price Index, Employment Level and Unemployment Level were recorded in monthly increments. These metrics were averaged together to create quarterly metrics for each time period. The United States Quarterly Gross Domestic Product (GDP) was recorded from the Bureau of Economic Analysis. The data range spanned from the first quarter of 2000 until the first quarter of 2017.

To determine whether the economic variables have leading, lagging or coincident impacts on the booking window, SAS 9.4 was used to run cross correlations between the economic series and the average quarterly booking window. Three properties that had the longest time series (2009, 2011 – 2016) were used to determine which variables were leading or lagging with comparisons running 2 years (8 quarters). The results of the cross correlations revealed the strongest relationships between the independent and dependent variable in Table 2 to be included in the model. Similar to the study conducted by Choi (2003), GDP was identified as a coincident indicator while Total Employment and Unemployment were found to be lagging indicators. Results of the cross-correlation analysis are provided in the Appendix.

Table 2. – Cross-Correlation Results

Economic Variable	**CCF - Identified Lag**
CPI	4 Quarters / 1 Year
Employment	1 Quarter
Unemployment	2 Quarters
GDP	None/Coincident

Results

The results of the models are reported in Table 3. In each model, one economic indicator was paired with the percent of bookings made online for the given quarter. Several iterations of the model were run, however strong multicollinearity between the economic indicators required that only one economic variable be included to avoid biased parameter estimates. The results show that the percentage of online bookings did not have a significant effect on booking window lead times. In other words, technology is not driving the booking window shifts.

Interestingly, in all models the economic variables have a significant positive relationship on booking window lead times. The results would suggest that as the economy improves the booking windows expand and travelers tend to book further in advance. Similarly, as the economy contracts booking windows will shorten. This can likely be attributed to the fact that during strong economic times, increased financial security allows travelers to book further in advance with the confidence that they can afford the trip. To test for robustness, the models were re-estimated using the log of average booking window lead times to enhance normality of the dependent variable. The outcome of these models, provided in Table 4, show the same relationships that were obtained using the untransformed dependent variable. The results further validate the relationship of technological and economic variables on booking window lead times at these locations.

Table 3. – Regression Results: DV - Quarterly Booking Window

Variable	Parameter	Significance	Parameter	Significance	Parameter	Significance	Parameter	Significance
Intercept	-41.72	0.06	-187.82	0.00	87.11	<.0001	-135.97	0.01
% Reservations Online	**-14.06**	**0.34**	**-15.69**	**0.29**	**-16.13**	**0.29**	**-4.63**	**0.74**
Quarterly GDP	**0.01**	**<.0001**						
Quarterly Employment			**0.00**	**<.0001**				
Quarterly Unemployment					**-369.05**	**<.0001**		
Quarterly CPI							**0.83**	**0.00**
P1	81.79	<.0001	81.76	<.0001	81.75	<.0001	81.99	<.0001
P2	-9.91	0.16	-9.88	0.16	-9.85	0.16	-10.07	0.15
P3	15.11	0.03	15.30	0.03	15.19	0.03	14.63	0.04
P4	-16.00	0.02	-16.29	0.02	-16.29	0.02	-13.93	0.04
P5	2.64	0.75	3.18	0.70	3.17	0.71	0.09	0.99
P6	-13.52	0.04	-13.69	0.04	-13.73	0.04	-12.53	0.06
P7	-18.24	0.02	-18.13	0.02	-18.45	0.01	-17.36	0.02
P8	-6.26	0.34	-6.20	0.34	-6.18	0.34	-6.57	0.32
P9	-33.84	<.0001	-33.92	<.0001	-34.01	<.0001	-32.97	<.0001
P10	-15.78	0.03	-16.04	0.03	-16.26	0.03	-13.67	0.06
P11	-17.51	0.01	-17.35	0.01	-17.39	0.01	-18.01	0.01
P12	6.81	0.28	6.94	0.26	7.05	0.26	6.47	0.31
P13	-13.39	0.03	-14.91	0.02	-15.29	0.01	-12.53	0.05
P14	13.37	0.03	13.52	0.03	13.63	0.03	12.88	0.04
Q1	-18.28	<.0001	-18.65	<.0001	-19.04	<.0001	-19.33	<.0001
Q2	7.91	0.01	7.40	0.01	7.37	0.01	7.05	0.01
Q3	23.75	<.0001	23.70	<.0001	23.67	<.0001	23.23	<.0001
F Value	**42.13**	**<.0001**	**42.37**	**<.0001**	**42.1**	**<.0001**	**41.19**	**<.0001**
R2	**0.786**		**0.7869**		**0.7858**		**0.7821**	
R2 Adjusted	**0.7673**		**0.7683**		**0.7672**		**0.7631**	

Table 4. - Regression Results: DV – Log Quarterly Booking Window

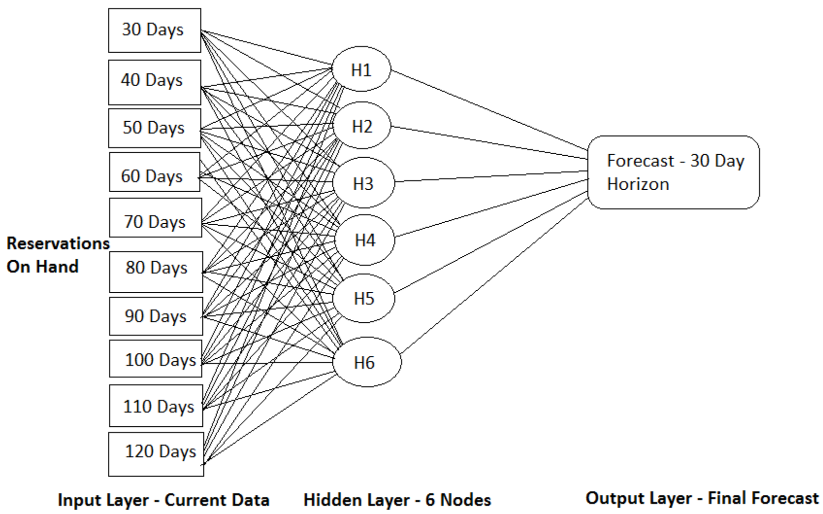
Variable	Parameter	Significance	Parameter	Significance	Parameter	Significance	Parameter	Significance
Intercept	2.00	<.0001	-0.84	0.36	4.63	<.0001	0.07	0.93
% Reservations Online	**-0.30**	**0.23**	**-0.30**	**0.23**	**-0.31**	**0.22**	**-0.10**	**0.67**
Quarterly GDP	**0.0001**	**<.0001**						
Quarterly Employment			**0.00003**	**<.0001**				
Quarterly Unemployment					**-7.36**	**<.0001**		
Quarterly CPI							**0.017**	**<.0001**
P1	0.76	<.0001	0.76	<.0001	0.76	<.0001	0.77	<.0001
P2	-0.23	0.05	-0.23	0.05	-0.23	0.06	-0.23	0.05
P3	0.21	0.08	0.21	0.07	0.21	0.08	0.20	0.10
P4	-0.31	0.01	-0.32	0.01	-0.32	0.01	-0.27	0.02
P5	-0.03	0.85	-0.02	0.86	-0.02	0.87	-0.08	0.57
P6	-0.22	0.05	-0.22	0.05	-0.22	0.05	-0.20	0.08
P7	-0.35	0.01	-0.35	0.01	-0.35	0.01	-0.33	0.01
P8	-0.20	0.07	-0.20	0.07	-0.20	0.07	-0.21	0.06
P9	-0.81	<.0001	-0.81	<.0001	-0.81	<.0001	-0.79	<.0001
P10	-0.31	0.01	-0.31	0.01	-0.31	0.01	-0.26	0.03
P11	-0.36	0.00	-0.36	0.00	-0.36	0.00	-0.37	0.00
P12	0.13	0.22	0.13	0.22	0.13	0.21	0.12	0.25
P13	-0.25	0.02	-0.28	0.01	-0.28	0.01	-0.23	0.03
P14	0.15	0.16	0.15	0.16	0.15	0.16	0.14	0.20
Q1	-0.50	<.0001	-0.51	<.0001	-0.51	<.0001	-0.53	<.0001
Q2	0.16	0.00	0.15	0.00	0.15	0.00	0.14	0.00
Q3	0.35	<.0001	0.35	<.0001	0.35	<.0001	0.34	<.0001
F Value	**41.44**	**<.0001**	**41.27**	**<.0001**	**49.26356**	**<.0001**	**40.01**	**<.0001**
R2	**0.7832**		**0.7825**		**0.7811**		**0.7771**	
R2 Adjusted	**0.7643**		**0.7635**		**0.7621**		**0.7577**	

Research Question 2

Methodology

To test the ability of neural networks to provide accurate forecasts in face of dynamic booking windows, the multi-layer perceptron (MLP) model was used to predict hotel room nights at four properties. The network architecture was designed similar to the curves similarity approach proposed by Schwartz and Hiemstra (1997) which used the reservations on hand every 10 days to identify similar booking curves. For example, the network architecture for the 30-day horizon would have inputs of reservations on hand at days 30, 40, 50, 60, 70, 80, 90, 100, 110 and 120 days prior to the date of stay (Figure 1). In addition to the thirty day horizon, 7 day (OTB 7, 17, 27, 37, 47, 57, 67, 77, 87, 97, 107, 127) and 14 day (OTB 14, 24, 34, 44, 54, 64, 74, 84, 94, 104, 114, 124) horizons were tested. These observations create the input vector for the neural network. Currently there is no clear-cut outline for full network architecture, however one hidden layer can account for non-linear relationships and Zhang (1998) states that one hidden layer should be sufficient for most forecasting problems. The number of nodes to be included in the hidden layer were identified based on which architecture minimized the average error and provided the lowest AIC, BIC. The activation and combination function used in the network were the standard functions recommended by SAS Enterprise Miner for interval data. Specifically, the hidden layer activation function was TanH (1-2/(1+e(2t))) while the combination function was linear (linear combination of incoming vales and weights). The target layer activation function utilized was the identity function.

Figure 1: Multi-Layer Perceptron Model



Multi-Layer Perceptron: Network Architecture

Several current data models that have been used in previous research were also estimated to test the accuracy of the MLP model. These models include additive pick-up, multiplicative pick-up, linear regression, log-linear regression, curves similarity and the polynomial curve fitting approach (Schwartz & Hiemstra, 1997; Weatherford & Kimes, 2003; Chen & Kachani, 2007; Tse & Poon, 2015). The formal derivations of each comparison model are provided below. Models 1-4 are designed to estimate the number of reservations to be picked up in the booking window from a fixed point in time. Model 5, the polynomial approach, fits a quadratic function to each booking curve and then extrapolates that curve from the current horizon to the date of stay. In this derivation, the model follows Tse & Poon (2015) which fits the curve starting 90 days prior to the date of stay, t = (90-n) where n is the number of days before the date of stay. This transformation allows the number of days to increase as the date of stay nears. Finally, the curve similarity derivation follows the approach of Schwartz & Hiemstra (1997) where the room nights on hand are compared every 10 days to identify historical dates of stay that have accumulated room nights in the same pattern. The final number of room nights of curves that are the 10 most similar (least dissimilarity) are averaged together to generate the final forecast.

Benchmark Models

1. Additive Pickup

$$Forecast_t = Current\ Reservations\ on\ Hand + Avg\ Pickup\ at\ Horizon$$

2. Multiplicative Pickup

$Forecast_t = (Current\ Reservations\ on\ Hand) * Avg\ Pickup\ Ratio$

3. Linear Regression

$$Forecast_t = a + b * Current\ Reservations\ on\ Hand$$

4. Log-Linear Regression

$$Log(Forecast_t) = a + b * Log(Current\ Reservations\ on\ Hand)$$

5. Polynomial Curve Fit

$$Forecast_t = a + bt + ct^2$$

Where t is defined as t = (90-n), and n is the number of days before the date of stay.

6. Curves Similarity

$$Dissimilarity = \sqrt{(R_{30} - C_{30})^2 + (R_{40} - C_{40})^2 + .. + (R_{110} - C_{110})^2 + (R_{120} - C_{120})^2}$$

Where R is a historical booking curves reservations at time t and C is the the current booking curves reservations at time t.

Final Forecast

$Forecast_t = Average\ 10\ most\ similar\ curves$

Evaluating the most accurate forecasting method across all techniques can be challenging as outlined by Koupriouchina et al (2014). The most accurate forecast can be misleading depending on the error measure used. The differences exist because of how the error measures are formulated. For this reason, the study implements three commonly accepted error metrics for comparison, specifically, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). In addition, each of the forecasts errors were statistically tested using the Wilcoxon Signed Rank Test, a non-parametric technique. The technique allows for the comparison of each model against one another to statistically imply the most accurate method by ranking the difference in results (Flores, 1989).

Formally

$$H_0: M_d = 0$$
$$H_1: M_d \neq 0$$

Where M_d is the sum of the signed ranks of the forecasting error metrics.

Data

To conduct the investigations, reservations data spanning multiple years was collected from four properties located in or around National Parks in the United States. Two properties were on the West Coast, while one location was in the North West and another in the Mid-West. The average booking window for each year and each quarter (displayed in Tables 5-8) was estimated to observe the change in booking windows to identify estimation and hold out samples.

Table 5. West Coast Property 1 – Reservation Average Lead Time

		Avg. Lead Days Prior to Arrival				
Property	**Quarter**	**2012**	**2013**	**2014**	**2015**	**2016**
West Coast P1	Q1	32	34	39	39	42
West Coast P1	Q2	67	68	69	85	73
West Coast P1	Q3	89	92	91	92	94
West Coast P1	Q4	53	51	61	58	62

Table 6. West Coast Property 2 – Reservation Average Lead Time

		Avg. Lead Days Prior to Arrival				
Property	**Quarter**	**2012**	**2013**	**2014**	**2015**	**2016**
West Coast P2	Q1	24	28	26	32	32
West Coast P2	Q2	69	76	83	93	93
West Coast P2	Q3	104	109	123	126	137
West Coast P2	Q4	42	38	50	53	61

Table 7. North West Property 1 – Reservation Average Lead Time

		Avg. Lead Days Prior to Arrival			
Property	**Quarter**	**2013**	**2014**	**2015**	**2016**
North West P1	Q1	27	20	23	26
North West P1	Q2	40	47	50	61
North West P1	Q3	79	90	112	117
North West P1	Q4	31	37	31	41

Table 8. Mid-West Property 1 – Reservation Average Lead Time

		Avg. Lead Days Prior to Arrival					
Property	**Quarter**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Midwest P1	Q1	23	21	25	28	26	36
Midwest P1	Q2	33	36	39	44	44	46
Midwest P1	Q3	49	50	50	56	63	67
Midwest P1	Q4	37	34	36	40	44	40

In all cases, it appears that the booking window tends to be increasing over time. As the focus of the study is to determine the most robust forecasting methods in the face of the dynamic booking windows, a model estimation period is selected for each property in early years that contains the shorter booking window. These years are highlighted in yellow for each table, for West Coast P1 and P2 the estimation period was 2012 and 2013, for North West P1 the estimation period was 2013 and 2014 and for Midwest P1 the estimation period was 2010 and 2011.

For each estimation period a holdout sample was selected to provide validity to the model estimates. Granger (1993) suggests a holdout sample of 20% for nonlinear forecasting models. Therefore, the estimation sample was 80% of the data and the holdout sample contained 20% of the data. The number of observations in each sample are displayed in Table 20. The derivation of the estimate and hold out samples was conducted using stratified random sampling in SAS with strata selected as the arrival month and day of week. These strata created estimation and hold out samples that spanned all months of the year and all days of the week.

A third sample was selected following the same procedure in a later time period when the booking window had shifted. These time periods are highlighted in red for Tables 5-8. For the properties denoted West Coast P1, P2 and Northwest P1 the sample was selected from 2016. For Midwest P1 the sample was selected from 2015.

Overall the sample selection process allows for model estimation and validation in one-time period to identify the best model and create a benchmark. Then the same estimated model is tested again on a future sample, years later, to determine the impacts that booking window shifts may have on forecasting accuracy and which models are most robust. Each property, model and sample were estimated on 3 different horizons of 7 days, 14 days, 30 days prior to the date of stay.

Table 9. Observations for Each Location

	Number of Observations		
Property	**Estimate**	**Hold Out**	**Booking Window**
Mid-West P1	562	168	168
North West P1	554	166	168
West Coast P1	563	168	168
West Coast P2	555	168	168

Results

The results of the forecasting models are displayed for each property in Tables 10-13. Each table reports the accuracy of each technique, across the three-error metrics, three horizons and the three samples. The Wilcoxon Signed Rank Test was also used to evaluate if significant differences existed between the forecasting techniques. The pairwise comparisons were conducted over all the properties, error metrics, horizons and hold out samples, compiling 1,512 observations. Results tended to be consistent across metrics and the results of the tests using absolute error (AE) are provided in the appendix.

Several models performed consistently well across all settings. Specifically, the multi-layer perceptron, log-regression and curve similarity techniques revealed the most accuracy as can be seen by the error values in Tables 10-13. To quantify the results, the counts of when the models statistically outperformed competing techniques across all properties, horizons and error measures are provided in Tables 14-19. In these tables, the models are listed on the left while the first column provides a count if the tested model outperforms the listed model at a 0.05 level of significance. The second column counts if the test revealed no statistical difference between the two models, while the third column reports if the competing model performed better at the 0.05 level of significance. For example, in Table 14 the Multi-Layer Perceptron model statistically outperformed regression ($p<0.05$) in 23 occurrences, while there was no statistically difference on 13 of the comparisons.

Reviewing the results of the Wilcoxon Tests with the holdout sample shows that MLP performs extraordinarily well. The technique completely dominates the performance of multiplicative pick-up and polynomial fitting techniques. When compared to the log-regression and curve similarity approach, the MLP generally does not outperform the two techniques. This suggests that the techniques are relatively comparable and would perform the same in most instances at these locations. Interestingly, the success of the MLP may be characterized in the sense that no other model statistically outperforms it in any comparison. This is the only model that had this outcome and implies the potential confidence a practitioner may have in exploring this technique.

The results of the Wilcoxon tests with log-regression show significantly better performance than regression, additive pick-up, multiplicative pick-up and polynomial fits in all instances. However, the technique rarely outperforms the curve similarity or MLP techniques. The curve similarity approach performs relatively similar to the MLP by outperforming competing techniques in a majority of instances with limited success in comparison to the log-regression and MLP techniques.

Transitioning to the sample with the shifted booking window, the forecast errors and Wilcoxon tests reveal some deterioration in performance from the initial hold out sample. The error results in Tables 10-13 suggest that the MLP, Log Regression and Curve Similarity approaches are generally the best performing models. The comparison of the models in the Wilcoxon tables reveal results that are further spread amongst the three best performing techniques, providing little preference to a superior model when the booking window shifts. Interestingly, the additive pick-up and multiplicative pick-up methods tend to perform better when compared to the MLP and Curve Similarities in some instances. This largely occurs at West Coast properties P1 and P2 where the booking window sample errors decrease from even the estimation errors. Although there is no explicit reason for the improvement, it could be concluded that as the booking window increased at these locations, less variability existed in the number of rooms picked up. In other words, the pick-up estimates at these time periods were closer to the average pick-up that was calculated during estimation. This may suggest that if the booking window expands, and reservation accumulations are stable, these pick-up methods may be suitable forecasting techniques.

When looking at results across all the properties, techniques, error metrics and horizons, there are a few other observations to note. The first is that the error estimates of the MLP deteriorate when moving from the estimate sample to the two holdout samples. This is likely due to the possibility of over fitting when estimating the neural network, which is not unusual as it is repetitively trained on the estimation set. Further network architectures and estimation techniques could be evaluated to determine a more adequate model. In addition, any deterioration still outperforms competing models which demonstrates its strength. A second observation is that the multiplicative pick-up and polynomial models tend to perform the worst in all instances. The multiplicative pick-up would suggest that using a pick-up ratio is not a recommended technique for practitioners. The polynomial model may perform poorly because the curve was extrapolated from each horizon fitted 90 days in advance. The estimation of the polynomial with data starting 90 days prior to the horizon was used following the initial work of Tse and Poon (2015). Estimations using different parts of the curve may reveal more accurate (30, 45, 60 days) curve fits for forecasting purposes. In their study, estimating the final forecast in more limited time frames had increased accuracy (Tse & Poon, 2015).

Table 10. West Coast Property 1 – Forecast Errors

West Coast P1 Estimate 2012-2013											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	12.7	8.1%	18.4	Regression	19.3	12.5%	27.2	Regression	35.5	27.5%	57.6
Log Regression	11.9	6.4%	18.2	Log Regression	17.9	9.4%	26.7	Log Regression	31.2	17.3%	57.4
Additive PU	12.9	7.2%	18.8	Additive PU	20.2	10.8%	28.1	Additive PU	37.2	22.3%	60.0
Multiplicative PU	20.0	9.5%	25.8	Multiplicative PU	33.5	15.4%	41.8	Multiplicative PU	101.8	40.6%	133.1
Curve Similarity	14.6	7.8%	25.4	Curve Similarity	18.1	9.5%	31.6	Curve Similarity	30.7	21.8%	56.8
Polynomial Reg	24.1	11.6%	34.0	Polynomial Reg	34.4	16.0%	48.5	Polynomial Reg	51.4	23.8%	82.1
MLP	9.5	5.7%	14.8	MLP	13.9	8.6%	18.9	MLP	27.5	20.3%	48.4

West Coast P1 Holdout 2012-2013											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	15.0	10.5%	26.9	Regression	20.0	15.5%	30.7	Regression	40.2	36.6%	66.9
Log Regression	13.8	7.2%	26.7	Log Regression	18.2	10.3%	30.2	Log Regression	34.3	20.6%	66.1
Additive PU	15.1	8.9%	26.8	Additive PU	20.8	12.6%	31.1	Additive PU	41.3	28.5%	69.1
Multiplicative PU	20.8	9.9%	30.8	Multiplicative PU	34.8	16.7%	43.9	Multiplicative PU	105.3	42.6%	140.3
Curve Similarity	16.3	8.4%	31.7	Curve Similarity	20.5	11.3%	40.5	Curve Similarity	32.4	27.3%	68.1
Polynomial Reg	28.0	13.3%	42.1	Polynomial Reg	38.2	18.2%	54.1	Polynomial Reg	60.6	26.6%	105.5
MLP	12.2	6.8%	25.0	MLP	18.8	12.1%	29.0	MLP	34.3	26.9%	67.9

West Coast P1 Booking Window Holdout 2016											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	10.1	4.7%	12.7	Regression	16.9	7.2%	29.0	Regression	32.2	14.5%	55.8
Log Regression	10.2	4.6%	12.8	Log Regression	16.5	6.9%	28.8	Log Regression	31.7	13.0%	57.3
Additive PU	11.2	4.8%	13.8	Additive PU	18.7	7.5%	29.9	Additive PU	37.0	14.9%	60.8
Multiplicative PU	21.6	8.4%	25.9	Multiplicative PU	36.6	14.1%	45.4	Multiplicative PU	118.8	45.3%	142.5
Curve Similarity	16.5	7.3%	27.0	Curve Similarity	19.3	8.4%	33.5	Curve Similarity	28.9	12.9%	50.8
Polynomial Reg	24.8	10.2%	33.8	Polynomial Reg	36.0	14.5%	55.1	Polynomial Reg	57.6	23.6%	83.5
MLP	12.1	5.6%	17.3	MLP	25.4	11.5%	37.9	MLP	31.0	15.3%	52.5

Table 11. West Coast Property 2 – Forecast Errors

West Coast P2 Estimate 2012-2013											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	6.6	24.3%	13.2	Regression	8.4	33.4%	15.1	Regression	12.1	42.0%	17.7
Log Regression	6.0	21.9%	13.1	Log Regression	7.4	28.8%	14.8	Log Regression	10.5	32.8%	16.9
Additive PU	6.9	22.3%	13.6	Additive PU	9.0	30.4%	15.9	Additive PU	13.0	36.7%	18.7
Multiplicative PU	10.5	27.0%	16.6	Multiplicative PU	16.4	41.2%	23.4	Multiplicative PU	30.3	57.4%	42.0
Curve Similarity	6.8	24.9%	13.3	Curve Similarity	7.8	27.6%	14.5	Curve Similarity	8.8	29.4%	15.3
Polynomial Reg	9.1	29.0%	16.3	Polynomial Reg	12.1	32.3%	19.4	Polynomial Reg	18.7	40.5%	26.6
MLP	4.2	14.0%	7.3	MLP	4.6	10.7%	7.2	MLP	5.7	13.0%	9.4

West Coast P2 Holdout 2012-2013											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	7.9	28.8%	16.6	Regression	10.1	42.4%	19.3	Regression	13.7	55.6%	20.5
Log Regression	7.3	25.2%	16.4	Log Regression	8.8	35.5%	18.8	Log Regression	11.3	42.7%	19.4
Additive PU	8.2	25.1%	16.9	Additive PU	10.5	36.0%	20.1	Additive PU	13.7	47.1%	21.1
Multiplicative PU	11.6	28.9%	19.7	Multiplicative PU	17.4	46.1%	27.0	Multiplicative PU	29.9	66.0%	42.2
Curve Similarity	8.4	36.6%	17.1	Curve Similarity	8.9	40.2%	17.5	Curve Similarity	9.4	43.8%	17.2
Polynomial Reg	9.8	32.3%	19.1	Polynomial Reg	12.4	39.4%	21.0	Polynomial Reg	19.0	48.8%	27.1
MLP	7.6	16.7%	14.6	MLP	9.3	38.9%	19.7	MLP	9.7	43.8%	18.9

West Coast P2 Booking Window Holdout 2016											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	4.9	7.1%	7.4	Regression	6.1	9.5%	9.0	Regression	9.2	14.1%	11.5
Log Regression	4.6	6.8%	7.2	Log Regression	5.8	8.4%	8.7	Log Regression	8.7	11.8%	11.0
Additive PU	5.2	7.5%	7.8	Additive PU	7.7	10.4%	10.3	Additive PU	11.7	14.9%	14.2
Multiplicative PU	11.0	13.9%	13.2	Multiplicative PU	19.8	23.7%	22.8	Multiplicative PU	41.8	46.8%	50.9
Curve Similarity	6.6	9.3%	9.9	Curve Similarity	7.4	10.8%	10.4	Curve Similarity	7.9	11.6%	11.0
Polynomial Reg	9.5	13.0%	12.1	Polynomial Reg	12.2	16.4%	15.2	Polynomial Reg	18.1	23.8%	24.4
MLP	6.1	8.5%	9.1	MLP	9.4	13.1%	17.6	MLP	9.6	13.2%	20.4

Table 12. North West Property 1 – Forecast Errors

North West P1 Estimate 2013-2014											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	4.2	12.9%	7.0	Regression	5.1	17.0%	7.9	Regression	7.1	24.9%	9.3
Log Regression	4.1	11.9%	7.0	Log Regression	4.8	14.8%	7.7	Log Regression	6.1	19.1%	8.6
Additive PU	4.3	13.5%	7.0	Additive PU	5.1	16.5%	7.9	Additive PU	7.4	23.3%	9.5
Multiplicative PU	6.0	15.0%	8.6	Multiplicative PU	9.5	23.1%	12.6	Multiplicative PU	23.1	48.7%	31.3
Curve Similarity	4.3	13.2%	7.4	Curve Similarity	4.8	16.1%	7.9	Curve Similarity	6.1	20.8%	9.1
Polynomial Reg	7.0	19.0%	9.6	Polynomial Reg	8.1	22.1%	10.8	Polynomial Reg	12.1	32.5%	15.1
MLP	3.7	11.7%	6.0	MLP	3.7	13.5%	5.5	MLP	5.0	17.0%	7.4

North West P1 Holdout 2013-2014											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	3.7	9.7%	7.0	Regression	4.3	13.0%	7.5	Regression	6.0	20.7%	8.0
Log Regression	3.5	8.7%	6.9	Log Regression	4.0	11.0%	7.3	Log Regression	4.9	14.5%	7.0
Additive PU	3.8	10.5%	7.0	Additive PU	4.3	12.5%	7.5	Additive PU	5.9	18.3%	7.8
Multiplicative PU	5.4	11.5%	8.6	Multiplicative PU	8.5	18.7%	12.1	Multiplicative PU	21.8	43.8%	29.9
Curve Similarity	3.8	10.6%	6.9	Curve Similarity	4.3	12.7%	6.9	Curve Similarity	4.9	15.4%	7.3
Polynomial Reg	6.7	16.5%	9.7	Polynomial Reg	7.5	19.6%	10.4	Polynomial Reg	10.8	29.5%	13.4
MLP	3.8	9.4%	6.8	MLP	4.4	13.0%	7.3	MLP	5.5	16.1%	8.1

North West P1 Booking Window Holdout 2016											
Model - Horizon 7	MAE	MAPE	MSE	Model - Horizon 14	MAE	MAPE	MSE	Model - Horizon 30	MAE	MAPE	MSE
Regression	3.6	8.9%	4.6	Regression	4.9	12.0%	6.6	Regression	7.2	18.0%	8.8
Log Regression	3.5	8.5%	4.5	Log Regression	4.6	11.5%	6.2	Log Regression	6.2	15.7%	7.9
Additive PU	3.5	9.1%	4.6	Additive PU	5.0	12.0%	6.7	Additive PU	8.1	18.8%	9.8
Multiplicative PU	6.4	12.9%	8.1	Multiplicative PU	11.4	22.5%	14.3	Multiplicative PU	29.5	53.9%	40.2
Curve Similarity	4.2	10.8%	5.6	Curve Similarity	5.0	13.1%	6.7	Curve Similarity	6.0	16.3%	8.0
Polynomial Reg	6.2	14.3%	7.7	Polynomial Reg	7.7	18.2%	9.3	Polynomial Reg	11.8	28.3%	14.3
MLP	3.3	8.1%	4.4	MLP	6.2	16.0%	9.0	MLP	6.5	17.6%	9.0

Table 13. Mid-West Property 1 – Forecast Errors

Midwest P1 Estimate 2012-2013											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	6.8	16.1%	8.9	Regression	9.8	24.2%	12.6	Regression	15.8	42.4%	19.7
Log Regression	6.1	12.2%	8.3	Log Regression	8.3	16.7%	11.5	Log Regression	13.2	27.3%	17.9
Additive PU	6.8	15.8%	8.9	Additive PU	9.8	24.4%	12.6	Additive PU	16.1	45.4%	19.8
Multiplicative PU	12.3	18.1%	17.0	Multiplicative PU	22.0	29.3%	31.8	Multiplicative PU	46.5	58.3%	71.2
Curve Similarity	5.5	12.6%	7.8	Curve Similarity	6.5	15.6%	9.8	Curve Similarity	10.4	25.6%	14.7
Polynomial Reg	11.4	21.3%	15.2	Polynomial Reg	15.0	27.0%	20.2	Polynomial Reg	23.3	39.9%	31.4
MLP	3.8	10.0%	5.7	MLP	5.4	13.6%	7.9	MLP	8.1	21.8%	12.1

Midwest P1 Holdout 2012-2013											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	7.3	16.6%	9.9	Regression	10.6	25.3%	14.8	Regression	16.5	44.5%	20.5
Log Regression	6.5	12.6%	9.2	Log Regression	9.4	18.6%	13.9	Log Regression	14.1	29.3%	19.5
Additive PU	7.3	16.3%	9.9	Additive PU	10.6	25.5%	14.8	Additive PU	16.7	47.5%	20.4
Multiplicative PU	12.1	18.2%	17.2	Multiplicative PU	22.6	31.3%	33.0	Multiplicative PU	47.9	61.5%	73.9
Curve Similarity	5.5	12.6%	8.7	Curve Similarity	7.3	16.5%	12.7	Curve Similarity	11.0	27.7%	17.3
Polynomial Reg	12.1	22.9%	16.2	Polynomial Reg	15.3	27.9%	21.3	Polynomial Reg	22.2	39.6%	29.9
MLP	5.7	12.6%	8.6	MLP	7.4	17.4%	12.3	MLP	12.5	32.1%	19.6

Midwest P1 Holdout 2015											
Model - Horizon 7	**MAE**	**MAPE**	**MSE**	**Model - Horizon 14**	**MAE**	**MAPE**	**MSE**	**Model - Horizon 30**	**MAE**	**MAPE**	**MSE**
Regression	6.7	13.3%	8.7	Regression	10.2	20.5%	12.9	Regression	15.4	34.7%	18.9
Log Regression	6.1	10.7%	8.2	Log Regression	9.0	16.1%	11.9	Log Regression	13.1	25.2%	16.9
Additive PU	6.7	13.2%	8.8	Additive PU	10.1	20.6%	12.9	Additive PU	15.2	36.1%	18.4
Multiplicative PU	14.0	17.8%	19.0	Multiplicative PU	27.6	33.6%	37.8	Multiplicative PU	62.5	72.8%	91.7
Curve Similarity	5.3	10.9%	8.0	Curve Similarity	6.5	13.4%	10.4	Curve Similarity	8.8	21.8%	12.5
Polynomial Reg	9.9	16.8%	13.4	Polynomial Reg	13.9	22.8%	19.0	Polynomial Reg	22.7	34.7%	30.4
MLP	5.5	10.6%	8.5	MLP	7.7	16.2%	11.7	MLP	10.8	22.9%	16.8

Table 14. MLP – Wilcoxon Hold Out Performance

Model	Curve Similarity	No Difference	Other
Regression	23	13	0
Log Regression	8	28	0
Add PU	22	14	0
Mult PU	36	0	0
Curve Similarity	3	33	0
Poly Fit	36	0	0
MLP	0	0	0

Table 15. Log Regression – Wilcoxon Hold Out Performance

Model	Curve Similarity	No Difference	Other
Regression	36	0	0
Log Regression	0	0	0
Add PU	36	0	0
Mult PU	36	0	0
Curve Similarity	2	23	11
Poly Fit	36	0	0
MLP	0	28	8

Table 16. Curve Similarity – Wilcoxon Hold Out Performance

Model	Curve Similarity	No Difference	Other
Regression	22	14	0
Log Regression	11	23	2
Add PU	23	13	0
Mult PU	35	1	0
Curve Similarity	0	0	0
Poly Fit	36	0	0
MLP	0	33	3

Table 17. MLP – Wilcoxon Booking Window Performance

Model	Curve Similarity	No Difference	Other
Regression	16	12	8
Log Regression	8	18	10
Add PU	18	15	3
Mult PU	36	0	0
Curve Similarity	6	24	6
Poly Fit	36	0	0
MLP	0	0	0

Table 18. Log Regression – Wilcoxon Booking Window Performance

Model	Curve Similarity	No Difference	Other
Regression	16	20	0
Log Regression	0	0	0
Add PU	33	3	0
Mult PU	36	0	0
Curve Similarity	15	11	10
Poly Fit	36	0	0
MLP	10	18	8

Table 19. Log Regression – Wilcoxon Booking Window Performance

Model	Curve Similarity	No Difference	Other
Regression	18	6	12
Log Regression	10	11	15
Add PU	18	12	6
Mult PU	36	0	0
Curve Similarity	0	0	0
Poly Fit	36	0	0
MLP	6	24	6

Research Question 3

Methodology

The forecast models and results from research question two were leveraged to answer research question three; whether techniques that leverage the accumulation of reservations are more robust over time. The techniques that exhibit the Markov Property and don't utilize the booking curve are Models 1-4. Specifically, models 1-4 estimate a pick up from a specific point in time based on historical pick up trends. These techniques ignore how the reservations accumulated prior to the forecasting date. Models 5, 6, and the proposed MLP utilize information in how the reservations accumulate at previous time intervals and leverages that information to generate a forecast.

To statistically identify which models were better suited to combat dynamic booking windows, the pairwise t-test was implemented to compare the error measures in the hold out sample to the error measures in the shifted booking window identified in research question two. The results of each t-test were aggregated across all properties, error metrics and horizons to identify the general trends. Differences between the two error metrics were measured at the 0.05 level of significance. Techniques that prove to be more robust will not have a significant change in error metric between the two time periods.

Formally

$$H_0: \mu_d = 0$$
$$H_1: \mu_d \neq 0$$

Where μ_d is the mean difference between the average error in the hold out sample and the average error in the sample with the shifted booking window.

Data

The data used to compare the error metrics are the same samples and error metrics identified in research question two.

Results

The results of the aggregated t-tests are provided in Table 20. The forecasting models with the most consistent error metrics between samples were the Curve Similarity, Polynomial and MLP models. These models had the least number of significant differences ($p<0.05$) between error metrics. In addition, these methods all leverage the information provided in the booking curve and consider how reservations accumulate. The results of the tests may imply that when forecasting in locations with fluctuating booking windows, the curve based approaches provide more consistent estimates than the non-curve based pick-up methods. This may suggest that the curve based techniques are more robust over time and may be less susceptible to economic shocks or large booking window shifts. This is likely due to the macro and micro factors influencing when purchases are occurring and inherently included in how reservations have accumulated up until the forecast date. If a location can estimate a suitable curve based approach, then these findings would suggest that the approach would be more consistent over time.

Table 20. T-Test Results

Forecast	Significant	Insignificant
Regression	12	24
Log Regression	10	26
Additive Pick-Up	11	25
Multiplicative Pick-Up	11	25
Curve Similarity	3	33
Polynomial	5	31
Multi-Layer Perceptron	4	32

Conclusion

The results of the study have significant implications for hospitality and revenue management practices. Identifying when customers are likely to book is an important aspect of revenue management when considering which rate levels or restrictions to open or close. If the wrong decision is made, revenues can be negatively impacted. For instance, if demand does not pick up as expected, inventory may be categorized as distressed earlier, while the inventory is not actually distressed, but rather customers are simply booking at a different time. The results of research question one show that economic variables had a significant positive effect on booking lead times. In other words, as the economy improves (by any metric provided) the booking window lead time expands. This result agrees with findings from previous research in that not only a stronger economy indicates additional bookings but also encourages consumers to book earlier. This is likely due to stronger consumer confidence in their ability to afford a trip and proceed with the booking. For practitioners, the knowledge regarding how economic conditions influence reservation lead times can assist revenue managers with which pricing levers to pull and when.

The lack of influence of technology on booking window lead time contradicts the popular belief that the booking window continues to "shrink". One explanation for the lack of influence could be because the earliest observation is from 2009, nearly ten years after the emergence of OTA's. The suggested decline in booking window lead time may have been more pronounced in the past when consumer adoption of online booking gained momentum. The studies sample uses data largely after 2010 when the transition of consumers booking in the online environment has already come to fruition. Therefore, one could hypothesize that the influence of technology was more pronounced in the past. A second possible explanation is that although technology reduces the information gap and uncertainty associated with travel, providers have leveraged the power of technology through communication. By leveraging a direct communication line with potential travelers, they can introduce strategies to encourage bookings earlier. These strategies may include price signaling that rates are likely to increase or advertising that there is only one room left. In this scenario, although technology provides consumers the ability to delay a purchase, the strategies used by companies to encourage a purchase counteract the potential delay, causing no change in reservation lead time from technology.

Forecasting in dynamic booking windows presents significant challenges to practitioners because these forecasts feed revenue management optimization algorithms and dictate rate decisions. The importance of an accurate forecast cannot be understated as error reduction can contribute significant increases in revenue (Koupriouchina et al. 2014). The results of research question two would suggest that using a multi-layer perceptron model may provide revenue management practitioners with another suitable forecasting approach. Neural networks can model any type of data (categorical or interval) while also relaxing several assumptions required for many forecasting approaches. The simple architecture in this study leveraging current data as the input vector could be enhanced by adding additional data points such as, the day of week, month, or historical totals on similar days for increased accuracy.

With regards to the importance of including how reservations accumulate in forecasting model estimations, the results of research question three suggests that curve based approaches provide more robust models. While it is recommended that practitioners evaluate a range of methods for forecasting in dynamic booking windows, the results show that these models are less impacted by changes in the booking window lead time and should provide practitioners with increased accuracy over a longer duration. These results are likely attributed to the fact that how the reservations accumulate prior to the forecast help to depict the current consumption climate as well as the macro and micro factors that may be influencing the pace of booking. Leveraging information from previous curves that follow the same pattern, allows for model estimation on data from bookings that may have occurred under similar conditions in the past. The results of this study suggest that industry professionals who use curve based forecasting approaches will likely experience more accurate forecasts over time. These techniques will also require less re-estimation in comparison to the traditional pick up methods, thus providing a more autonomous forecasting system.

Limitations

There are several limitations of the study that should be considered when interpreting results. In the regression analysis, the booking window shifts are analyzed across 15 properties which should not be considered an accurate representation of all properties in the United States. The results and patterns for booking window behavior may be different at properties not located in and around national parks. As the focus of the study was to try and observe leisure traveler booking patterns, the results may be different for properties located in urban and suburban areas that have different types of guests such as business travelers with different booking behaviors.

The forecasting analysis also has several limitations as the models were estimated on only four properties located around national parks. The accuracy of the models may provide different results for properties located in different geographic locations with different targeted markets. The goal of focusing on leisure travelers and their shifts in booking behavior was met with the national parks data used in this study, however, further investigation is necessary to formally suggest the most robust forecasting methods for hotel reservations.

Future Research

Several areas of future research are present from the results of this study. The first is the importance of the economy in booking window fluctuations and travel purchase patterns. Leveraging economic indicators into the forecasting models may prove more accurate for forecasting in dynamic booking windows and help account for their shifts. A second area of future research is the lack of shift in booking behavior due to technology. The results allow one to hypothesize that the shift in booking behavior due to technology may have been more pronounced in the past. Obtaining a data set with reservation accumulations prior to internet reservations, as well as when internet reservations took off may further confirm that the large booking window shift occurred years back and is not significant today. A third area for future research is a further investigation into the benefits of neural networks for forecasting in hospitality revenue management. Several other techniques such as the Kohonen Self Organizing Map (SOM) may prove superior for forecasting with current data and identifying booking window patterns. In addition, hospitality research has yet to leverage neural networks to combine the three data techniques (historical, current and exogenous information) for revenue management purposes. Specifically, studies tend to generate weighted averages of different forecasting techniques to construct a final forecast. Neural networks may be able find the optimal combinations of the data without having to estimate and test combinations of all the different data techniques. In this instance, neural networks may provide a solution for combining forecasting techniques together.

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Appendix

Appendix A – Cross Correlation Results

Property 1T - CPI, Lead Days		
LAG	N	CCF
-8	17	-0.15
-7	18	-0.08
-6	19	0.01
-5	20	0.00
-4	21	-0.06
-3	22	-0.03
-2	23	0.07
-1	24	0.08
0	24	0.08
1	24	0.08
2	24	0.09
3	24	0.10
4	24	0.11
5	24	0.10
6	24	0.11
7	24	0.11
8	24	0.11

Property 1T - Employment, Lead Days		
LAG	N	CCF
-8	17	-0.08
-7	18	0.04
-6	19	0.18
-5	20	0.16
-4	21	0.06
-3	22	0.14
-2	23	0.29
-1	24	0.28
0	24	0.28
1	24	0.29
2	24	0.28
3	24	0.25
4	24	0.24
5	24	0.24
6	24	0.21
7	24	0.17
8	24	0.15

Property 1T - Unemploy Rate, Lead Days		
LAG	N	CCF
-8	17	-0.07
-7	18	-0.12
-6	19	-0.19
-5	20	-0.20
-4	21	-0.16
-3	22	-0.20
-2	23	-0.28
-1	24	-0.28
0	24	-0.27
1	24	-0.30
2	24	-0.30
3	24	-0.29
4	24	-0.28
5	24	-0.29
6	24	-0.26
7	24	-0.22
8	24	-0.16

Property 1T - GDP, Lead Days		
LAG	N	CCF
-8	16	-0.06
-7	17	-0.14
-6	18	-0.05
-5	19	0.07
-4	20	0.06
-3	21	-0.03
-2	22	0.02
-1	23	0.15
0	24	0.15
1	24	0.14
2	24	0.13
3	24	0.14
4	24	0.15
5	24	0.13
6	24	0.14
7	24	0.14
8	24	0.13

Property 2G - CPI, Lead Days		
LAG	N	CCF
-8	17	-0.15
-7	18	-0.14
-6	19	-0.02
-5	20	0.00
-4	21	-0.08
-3	22	-0.05
-2	23	0.05
-1	24	0.05
0	24	0.05
1	24	0.05
2	24	0.05
3	24	0.05
4	24	0.06
5	24	0.06
6	24	0.06
7	24	0.06
8	24	0.06

Property 2G - Employment, Lead Days		
LAG	N	CCF
-8	17	-0.16
-7	18	-0.12
-6	19	0.06
-5	20	0.08
-4	21	-0.03
-3	22	0.05
-2	23	0.22
-1	24	0.18
0	24	0.17
1	24	0.19
2	24	0.18
3	24	0.15
4	24	0.15
5	24	0.15
6	24	0.13
7	24	0.11
8	24	0.10

Property 2G - Unemploy Rate, Lead Days		
LAG	N	CCF
-8	17	0.01
-7	18	0.00
-6	19	-0.08
-5	20	-0.09
-4	21	-0.05
-3	22	-0.09
-2	23	-0.17
-1	24	-0.16
0	24	-0.16
1	24	-0.19
2	24	-0.19
3	24	-0.18
4	24	-0.17
5	24	-0.18
6	24	-0.17
7	24	-0.14
8	24	-0.09

Property 2G - GDP, Lead Days		
LAG	N	CCF
-8	16	-0.07
-7	17	-0.16
-6	18	-0.15
-5	19	0.01
-4	20	0.03
-3	21	-0.07
-2	22	-0.03
-1	23	0.10
0	24	0.10
1	24	0.08
2	24	0.08
3	24	0.09
4	24	0.09
5	24	0.08
6	24	0.08
7	24	0.09
8	24	0.09

Property 3O - CPI, Lead Days		
LAG	N	CCF
-8	25	-0.10
-7	26	-0.07
-6	27	0.06
-5	28	0.06
-4	29	0.04
-3	30	0.08
-2	31	0.17
-1	32	0.19
0	32	0.19
1	32	0.19
2	32	0.18
3	32	0.19
4	32	0.20
5	32	0.20
6	32	0.20
7	32	0.21
8	32	0.23

Property 3O - Employment, Lead Days		
LAG	N	CCF
-8	25	0.14
-7	26	0.21
-6	27	0.39
-5	28	0.37
-4	29	0.33
-3	30	0.39
-2	31	0.50
-1	32	0.47
0	32	0.44
1	32	0.40
2	32	0.34
3	32	0.27
4	32	0.22
5	32	0.17
6	32	0.11
7	32	0.07
8	32	0.03

Property 3O - Unemploy Rate, Lead Days		
LAG	N	CCF
-8	25	-0.30
-7	26	-0.34
-6	27	-0.43
-5	28	-0.44
-4	29	-0.44
-3	30	-0.48
-2	31	-0.53
-1	32	-0.51
0	32	-0.47
1	32	-0.42
2	32	-0.35
3	32	-0.28
4	32	-0.19
5	32	-0.12
6	32	-0.04
7	32	0.03
8	32	0.10

Property 3O - GDP, Lead Days		
LAG	N	CCF
-8	24	-0.02
-7	25	-0.04
-6	26	0.00
-5	27	0.15
-4	28	0.15
-3	29	0.12
-2	30	0.16
-1	31	0.27
0	32	0.28
1	32	0.27
2	32	0.25
3	32	0.25
4	32	0.25
5	32	0.22
6	32	0.21
7	32	0.21
8	32	0.21

Appendix B - Absolute Error Wilcoxon Test Results

The results of the Wilcoxon Signed Rank Tests are provided in the corresponding tables. The estimate of the metric infers which method may be superior based on how the test was performed. A negative sign implies the model on the left-hand side of the table is more accurate while a positive sign indicates the model on the top is more accurate. The p-values are recorded in the sequential table which depicts if the model is superior to the others.

Wilcoxon Test - Mid West P1 - HO Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2705.5	-220	-2386.5	2553	-4115	2415
Log Regression	-	-	-3043	-3262	1554.5	-5002	1197
Add PU	-	-	-	-2440	2526.5	-4170	2373
Mult PU	-	-	-	-	3040.5	-1094	3110
Curve Similarity	-	-	-	-	-	-5062	-578
Poly Fit	-	-	-	-	-	-	5064
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.729	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.013	0.000	0.058
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.083	0.000
Curve Similarity	-	-	-	-	-	0.000	0.362
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - Mid West P1 - HO Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3112	-610.5	-3086.5	3396	-3018	2729
Log Regression	-	-	-3069	-4103.5	2529	-4397	1687
Add PU	-	-	-	-3062	3411.5	-2995	2746
Mult PU	-	-	-	-	4173	1264	4267
Curve Similarity	-	-	-	-	-	-4831	-551
Poly Fit	-	-	-	-	-	-	4687
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.335	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.000	0.000	0.007
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.045	0.000
Curve Similarity	-	-	-	-	-	0.000	0.384
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - Mid West P1 - HO Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3294.5	-1542.5	-2986	3689	-2183	2629
Log Regression	-	-	-2814.5	-3765.5	2093.5	-3652.5	1363.5
Add PU	-	-	-	-2819	3821.5	-1951	2815
Mult PU	-	-	-	-	4461.5	2125.5	3828
Curve Similarity	-	-	-	-	-	-4570	-1011
Poly Fit	-	-	-	-	-	-	3734
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.014	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.001	0.000	0.026
Add PU	-	-	-	0.000	0.000	0.002	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.110
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - Mid West P1 - BW Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2849.5	-939.5	-3484.5	2416	-2882	2447
Log Regression	-	-	-3297.5	-4161.5	1551	-3656	1630
Add PU	-	-	-	-3523.5	2409.5	-2884	2427
Mult PU	-	-	-	-	3486	1757	3506.5
Curve Similarity	-	-	-	-	-	-3880	-162
Poly Fit	-	-	-	-	-	-	3714
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.137	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.014	0.000	0.009
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.005	0.000
Curve Similarity	-	-	-	-	-	0.000	0.798
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - Mid West P1 - BW Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3680.5	984.5	-4232	3750	-2575	2578
Log Regression	-	-	-3537	-4986.5	2844.5	-3677	1431
Add PU	-	-	-	-4221.5	3758	-2574	2587
Mult PU	-	-	-	-	5209.5	3054	4477
Curve Similarity	-	-	-	-	-	-4420	-1983
Poly Fit	-	-	-	-	-	-	3818
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.119	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.000	0.000	0.023
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.002
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - Mid West P1 - BW Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3783.5	32.5	-4238.5	4102	-2725	3487
Log Regression	-	-	-2572	-4904	2938	-4110	2500
Add PU	-	-	-	-4153.5	4175	-2758	3459
Mult PU	-	-	-	-	5365	3730	5421
Curve Similarity	-	-	-	-	-	-4832	-966
Poly Fit	-	-	-	-	-	-	4029
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.959	0.000	0.000	0.000	0.000
Log Regression	-	-	0.000	0.000	0.000	0.000	0.000
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.126
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - HO Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2115	-963	-3189.5	187	-3907	2285
Log Regression	-	-	-4050.5	-4294	-871	-4885	1255
Add PU	-	-	-	-3537.5	452.5	-4103	2515
Mult PU	-	-	-	-	2782	-2215	4214
Curve Similarity	-	-	-	-	-	-4105	1836
Poly Fit	-	-	-	-	-	-	5009
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.001	0.128	0.000	0.768	0.000	0.000
Log Regression	-	-	0.000	0.000	0.168	0.000	0.047
Add PU	-	-	-	0.000	0.475	0.000	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.003
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - HO Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1672.5	-1843.5	-4224.5	1320	-3800	934
Log Regression	-	-	-4578.5	-5177	52	-4707	-263
Add PU	-	-	-	-4663	1833.5	-3805	1470
Mult PU	-	-	-	-	4421	-20	4110
Curve Similarity	-	-	-	-	-	-4301	-860
Poly Fit	-	-	-	-	-	-	3830
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.008	0.003	0.000	0.036	0.000	0.140
Log Regression	-	-	0.000	0.000	0.935	0.000	0.678
Add PU	-	-	-	0.000	0.003	0.000	0.019
Mult PU	-	-	-	-	0.000	0.975	0.000
Curve Similarity	-	-	-	-	-	0.000	0.174
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - HO Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1686	-499	-4502	3084	-2217	2003
Log Regression	-	-	-4413	-5253.5	1471	-3687	586
Add PU	-	-	-	-4886.5	2650.5	-2187	2119
Mult PU	-	-	-	-	5166	3608	4957
Curve Similarity	-	-	-	-	-	-3547	-898
Poly Fit	-	-	-	-	-	-	3096
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.007	0.431	0.000	0.000	0.000	0.001
Log Regression	-	-	0.000	0.000	0.019	0.000	0.355
Add PU	-	-	-	0.000	0.000	0.000	0.001
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.156
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - BW Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	-55	-3107.5	-5408	-2832	-4544	-679
Log Regression	-	-	-3198	-5579	-2947	-4664	-810
Add PU	-	-	-	-5589	-2100	-4269	46
Mult PU	-	-	-	-	2626	-720	4093
Curve Similarity	-	-	-	-	-	-2892	2391
Poly Fit	-	-	-	-	-	-	4191
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.931	0.000	0.000	0.000	0.000	0.284
Log Regression	-	-	0.000	0.000	0.000	0.000	0.200
Add PU	-	-	-	0.000	0.001	0.000	0.942
Mult PU	-	-	-	-	0.000	0.255	0.000
Curve Similarity	-	-	-	-	-	0.000	0.000
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - BW Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1212	-2936.5	-5354	-1066	-4292	-2453
Log Regression	-	-	-3502.5	-5655	-1475	-4485	-2723
Add PU	-	-	-	-5671	-163	-3847	-1801
Mult PU	-	-	-	-	4147	714	2990
Curve Similarity	-	-	-	-	-	-3845	-1529
Poly Fit	-	-	-	-	-	-	2085
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.055	0.000	0.000	0.091	0.000	0.000
Log Regression	-	-	0.000	0.000	0.019	0.000	0.000
Add PU	-	-	-	0.000	0.797	0.000	0.004
Mult PU	-	-	-	-	0.000	0.259	0.000
Curve Similarity	-	-	-	-	-	0.000	0.015
Poly Fit	-	-	-	-	-	-	0.001
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P1 - BW Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	143	-2720.5	-5847	1435	-4445	501
Log Regression	-	-	-3910	-6084.5	1120	-4812	586
Add PU	-	-	-	-5981	2429.5	-3534	1832
Mult PU	-	-	-	-	6244	4612	5996
Curve Similarity	-	-	-	-	-	-5026	-361
Poly Fit	-	-	-	-	-	-	4337
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.822	0.000	0.000	0.023	0.000	0.429
Log Regression	-	-	0.000	0.000	0.076	0.000	0.355
Add PU	-	-	-	0.000	0.000	0.000	0.003
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.569
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - HO Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2995.5	-923	-2726	167	-2108	459
Log Regression	-	-	-3777	-3486	-1055	-3406	-843
Add PU	-	-	-	-3071.5	600	-1959	930
Mult PU	-	-	-	-	2355	1419	2920
Curve Similarity	-	-	-	-	-	-1646	408
Poly Fit	-	-	-	-	-	-	1863
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.130	0.000	0.785	0.000	0.453
Log Regression	-	-	0.000	0.000	0.083	0.000	0.167
Add PU	-	-	-	0.000	0.326	0.001	0.127
Mult PU	-	-	-	-	0.000	0.019	0.000
Curve Similarity	-	-	-	-	-	0.007	0.505
Poly Fit	-	-	-	-	-	-	0.002
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - HO Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3532	-582	-2874.5	1316	-1644	1461
Log Regression	-	-	-4084	-3796	37.5	-3244	83
Add PU	-	-	-	-3471	1680	-1633	1567
Mult PU	-	-	-	-	3995	2134	3606
Curve Similarity	-	-	-	-	-	-2883	677
Poly Fit	-	-	-	-	-	-	2927
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.341	0.000	0.030	0.007	0.016
Log Regression	-	-	0.000	0.000	0.951	0.000	0.892
Add PU	-	-	-	0.000	0.005	0.007	0.010
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.268
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - HO Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	3719	196.5	-3003	3822	-1921	3798
Log Regression	-	-	-4870	-4196	1988	-3761	2377
Add PU	-	-	-	-3533	3350.5	-2110	3614
Mult PU	-	-	-	-	4801	2081	4766
Curve Similarity	-	-	-	-	-	-4525	239
Poly Fit	-	-	-	-	-	-	4507
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.748	0.000	0.000	0.001	0.000
Log Regression	-	-	0.000	0.000	0.001	0.000	0.000
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.001	0.000
Curve Similarity	-	-	-	-	-	0.000	0.696
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - BW Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1261.5	-1124	-5267.5	-1945	-4918	-1354
Log Regression	-	-	-2300	-5735	-2402	-5386	-1948
Add PU	-	-	-	-5616	-1021.5	-4833	-692
Mult PU	-	-	-	-	3992	1551	4363
Curve Similarity	-	-	-	-	-	-3055	490
Poly Fit	-	-	-	-	-	-	3552
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.045	0.075	0.000	0.002	0.000	0.032
Log Regression	-	-	0.000	0.000	0.000	0.000	0.002
Add PU	-	-	-	0.000	0.106	0.000	0.274
Mult PU	-	-	-	-	0.000	0.014	0.000
Curve Similarity	-	-	-	-	-	0.000	0.439
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - BW Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1021.5	-3036.5	-5834	-1264.5	-4307	-2028
Log Regression	-	-	-4297	-6173	-1574	-4756	-2467
Add PU	-	-	-	-5941	697.5	-3563	108
Mult PU	-	-	-	-	5635	4308	5169
Curve Similarity	-	-	-	-	-	-3562	-285
Poly Fit	-	-	-	-	-	-	2909
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.106	0.000	0.000	0.045	0.000	0.001
Log Regression	-	-	0.000	0.000	0.012	0.000	0.000
Add PU	-	-	-	0.000	0.271	0.000	0.865
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.653
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - West Coast P2 - BW Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1092.5	-3340.5	-5846	1744	-3695	1914
Log Regression	-	-	-5193	-6225	1282	-4078	1558
Add PU	-	-	-	-6070	3015.5	-2587	3437
Mult PU	-	-	-	-	6110	4896	5854
Curve Similarity	-	-	-	-	-	-4590	261
Poly Fit	-	-	-	-	-	-	4143
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.084	0.000	0.000	0.005	0.000	0.002
Log Regression	-	-	0.000	0.000	0.042	0.000	0.013
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.681
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - HO Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	1901.5	-1730.5	-2666	-187	-4775.5	410.5
Log Regression	-	-	-2080.5	-3325	-834	-4964.5	-254.5
Add PU	-	-	-	-2310	151	-4653.5	719.5
Mult PU	-	-	-	-	1841	-2295.5	2428.5
Curve Similarity	-	-	-	-	-	-4191.5	418.5
Poly Fit	-	-	-	-	-	-	4291.5
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.002	0.005	0.000	0.764	0.000	0.510
Log Regression	-	-	0.001	0.000	0.179	0.000	0.683
Add PU	-	-	-	0.000	0.808	0.000	0.247
Mult PU	-	-	-	-	0.003	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.501
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - HO Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2736	1252	-3488	330.5	-4209.5	147.5
Log Regression	-	-	-2339.5	-4120.5	-597.5	-4735.5	-580.5
Add PU	-	-	-	-3632	103.5	-4308.5	-45.5
Mult PU	-	-	-	-	3401.5	606.5	3254.5
Curve Similarity	-	-	-	-	-	-4170.5	-205.5
Poly Fit	-	-	-	-	-	-	3782.5
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.043	0.000	0.596	0.000	0.813
Log Regression	-	-	0.000	0.000	0.332	0.000	0.346
Add PU	-	-	-	0.000	0.868	0.000	0.942
Mult PU	-	-	-	-	0.000	0.325	0.000
Curve Similarity	-	-	-	-	-	0.000	0.741
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - HO Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	4047.5	466	-4520	2475	-4117.5	1231.5
Log Regression	-	-	-3194.5	-5193.5	506	-5152.5	-637.5
Add PU	-	-	-	-4792	1968.5	-4246.5	959.5
Mult PU	-	-	-	-	5271	2850.5	5068.5
Curve Similarity	-	-	-	-	-	-5099.5	-845.5
Poly Fit	-	-	-	-	-	-	4561.5
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.454	0.000	0.000	0.000	0.047
Log Regression	-	-	0.000	0.000	0.412	0.000	0.301
Add PU	-	-	-	0.000	0.001	0.000	0.122
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.174
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - BW Horizon - 7 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	594.5	1491	-3752	-1732.5	-4466	1281
Log Regression	-	-	107.5	-3907.5	-1869	-4374	1086
Add PU	-	-	-	-3530	-1963	-4547	990
Mult PU	-	-	-	-	2624	95	3698
Curve Similarity	-	-	-	-	-	-3327	2802
Poly Fit	-	-	-	-	-	-	4511
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.348	0.018	0.000	0.006	0.000	0.042
Log Regression	-	-	0.865	0.000	0.003	0.000	0.085
Add PU	-	-	-	0.000	0.002	0.000	0.117
Mult PU	-	-	-	-	0.000	0.881	0.000
Curve Similarity	-	-	-	-	-	0.000	0.000
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - BW Horizon - 14 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	2351	-2451	-4536.5	-438	-3837	-698
Log Regression	-	-	-2777.5	-4758.5	-991.5	-4161	-1094
Add PU	-	-	-	-4538	-210	-3705	-525
Mult PU	-	-	-	-	3869	2237	3217
Curve Similarity	-	-	-	-	-	-3630	-751
Poly Fit	-	-	-	-	-	-	2336
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.000	0.000	0.490	0.000	0.270
Log Regression	-	-	0.000	0.000	0.117	0.000	0.083
Add PU	-	-	-	0.000	0.741	0.000	0.407
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.235
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values

Wilcoxon Test - North West P1 - BW Horizon - 30 AE

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	4010.5	-3623	-4900	2133	-4174	1428
Log Regression	-	-	-4365.5	-5262	363	-5100	-77
Add PU	-	-	-	-4929.5	2962	-3311	2306
Mult PU	-	-	-	-	4894	3089	4920
Curve Similarity	-	-	-	-	-	-4993	-452
Poly Fit	-	-	-	-	-	-	4683
MLP	-	-	-	-	-	-	-

Wilcoxon Test Estimates

Model	Regression	Log Regression	Add PU	Mult PU	Curve Similarity	Poly Fit	MLP
Regression	-	0.000	0.000	0.000	0.001	0.000	0.023
Log Regression	-	-	0.000	0.000	0.567	0.000	0.903
Add PU	-	-	-	0.000	0.000	0.000	0.000
Mult PU	-	-	-	-	0.000	0.000	0.000
Curve Similarity	-	-	-	-	-	0.000	0.476
Poly Fit	-	-	-	-	-	-	0.000
MLP	-	-	-	-	-	-	-

Wilcoxon Test p-values