Building Forecasting Models for Restaurant Owners and Managers: A case study

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Abstract

Small business entrepreneurs like restaurant owners are at the constant mercy of fluctuating demand patterns. Many independent restaurateurs suffer from poor collection of data, limited resources, and lack of knowledge to build sophisticated forecasting models. They often use simple rules of thumb or simple moving averages to create naïve forecasts that do not serve them well. In this paper, we introduce a case with data from a small independent restaurant to show how they can use spreadsheet software like Excel to build a robust forecasting model that captures the trend and seasonality of their data. We analyze different forecasting models and compare the effectiveness of each using Mean Square Error (MSE).

Keywords: Time Series Forecasting, Small Business, Restaurant, Case Research Study

JEL Codes: A22, C53, C80

Introduction

According to the literature on the restaurant industry business cycles, the US demonstrated three cycles (peak to peak, or trough to trough) for the period of 1970 through 1998. The restaurant industry peaked in 1973, 1979 and 1989, and troughs were at 1970, 1974, 1980 and 1991 Choi et. al. (1999). The mean duration of this industry cycle, calculated either by peak to peak or trough to trough, is 7.3 years. This means the next peak would be 1996 or 1997, followed by 2003 or 2004 and finally 2010 or 2011 if the past trends take the same track. Other related service industries experience similar trends. For example, the hotel industry declined sharply after it reached the peaks. The mean duration for the contraction is about two years (1.7 years) and the mean duration for the expansion is about six years (5.7 years). The hotel industry led the general business cycle peaks by about 0.75 years on average and also led at troughs in the general business cycle by roughly 0.5 years (Jeong-Gil Choi et al., 1999). Given the nature of business cycles, an owner of a small restaurant in a small town would need good forecasts to plan for the changes in demand.

The importance of accurate and timely forecasts of sales is apparent at all levels for restaurant operations. Short-term sales levels are important for daily and weekly employee scheduling, especially where restaurants are dependent on part-time labor. Restaurants deal with very perishable products, and therefore, purchasing and inventory need to be accurately estimated. From a long-term perspective, menu development, employee hiring and training, and capital investment decisions (e.g. equipment, seating capacity and expansion) are directly linked to accurate forecasts. Accurate sales projections also impact the effectiveness and efficiency of marketing strategies and advertising.

Historically, forecasting of restaurant sales in the hospitality industry has been based on the manager or owner’s judgment (D.A. Cranage & W.P. Andrew, 1992). The mismatch between the importance of forecasting and the lack of the use of quantitative forecasting methods can be attributed to the fact that the majority of the restaurants are owned by independent restaurant owners who tend to lack the resources for the development and application of more quantitative and accurate forecasting models.

Since the trade-off between forecast accuracy and the cost of obtaining accurate forecasts is important for any restaurant owner, we propose different forecasting models for an independently owned bistro in Florence, South Carolina using data from 2006 – 2008. We implement the forecasting models in a spreadsheet package (Microsoft Excel) that is commonly available. We analyze the accuracy of these models using common error terms like Mean Square Error and Mean Absolute Deviation and show that restaurant owners can use these simple models to develop their own forecasts without the need for any external macroeconomic data. Thus, restaurant owners can simply use their own data they collect to make accurate, timely forecasts.

The next section is a brief literature review on the restaurant industry and trends in forecasting methods. Next, we discuss the data and forecasting methods. We then put forth our results, and the last section contains the conclusion and implications of this work.

Literature Review

Most restaurants in the U.S. are owned and operated by independent restaurant owners. Of the 235,701 full-service restaurants operating in the U.S. in 2013, 66% have fewer than twenty employees, and 88 percent of have fewer than fifty employees (US Census Bureau, 2013). In fact, according to the National Restaurant Association, 7 out of 10 restaurants are single-unit operations (National Restaurant Association, 2015). These smaller businesses typically have few resources to dedicate to statistical analysis when compared to their larger counterparts. However, if properly implemented, they could see similar benefits in staffing, inventory control and capital investment by generating accurate forecasts of their sales. Restaurant owners must weigh the benefits of each, in terms of forecasting accuracy, with the cost and complexity of their implementation. At a fundamental level, methods of forecasting can be broken down into qualitative and quantitative models.

The judgmental forecasting model is perhaps the most utilized qualitative forecasting method among independent restaurateurs. Since many independent restaurant owners have limited resources, their access to expert analysis is often constrained. Judgmental forecasting consists of intuitive predictions based on a manager's collective experience. This method is generally applied because it is the least expensive and because getting accurate economic and industrial information may be difficult to procure for the restaurant industry (D.A. Cranage & W.P. Andrew, 1992).

Numerous studies have been conducted on the accuracy of judgment versus statistical models. Studies conducted by Armstrong (1983), and Lee et.al. (1997) among many others show that quantitative methods provide better forecasts than judgment based methods. However, it has been shown that adding judgmental factors to more complex quantitative models can improve forecast accuracy (V. S. Lin, 2013).

Quantitative models can be broken down into pure (i.e. univariate) time series models and econometric (or causal) models. Econometric models utilize regression equations and exogenous (or external) explanatory variables to establish a causal relationship between the dependent variable (e.g. restaurant sales) and the independent variables, like disposable income, the consumer price index, and unemployment. These econometric models assume *a priori* relationships between variables based on established economic theory. One of the advantages of these models for the forecasting of restaurant sales is that the decision maker can logically formulate the model based on a cause and effect relationship between causal variables and future sales. Reynolds et. al (2013) find that econometric models can provide accurate forecasts of the restaurant industry as a whole. However, they acknowledge that a limitation of the study is the use of annualized, industry wide data. While this type of model may produce accurate industry wide forecasts, the utility for single restaurateur is left undetermined.

There are disadvantages in using these types of econometric models. First, they are generally too complex to implement correctly. In order to use the exogenous causal variable to forecast the dependent variable, the future values of the causal variables must first be predicted (M. Geurts & J. Kelly, 1986). Even when a lagged causal variable is used to predict sales a period ahead, the reported causal variable is often an estimated value that is later revised. Lastly, there is a continual need to gather external data, which makes these models expensive to use. There is also the danger that the relationship between dependent and independent variables are spurious and the problem of causal relationships changing over time, making it necessary to constantly update or redesign the model. These reasons make more complex, multivariate models expensive for the independent restaurant owner to implement.

A less costly quantitative model to create is a pure time series model. Time series models look for time patterns (trends, cycles and seasonal effects) in a single series of data that is captured over time and can be expressed in one or more mathematical equations. These mathematical relationships are used to project the historical time patterns in the data into the future. One of the benefits of these types of models is that they can be generated without external data. Restaurant owners/managers need not spend time nor money procuring external data on various economic variables that may have a causal relationship with the variable being forecasted. Thus, in this way, restaurant managers can create a quantitative forecast without significant cost by using their own data. Many studies have been conducted on the performance of econometric versus time series models in other applications (J. Buongiorno, L. Brannman, & T. Bark, 1984; J. G. De Gooijer & R. J. Hyndman, 2006; J. Du Preez & S. F. Witt, 2003; F.G. Forst, 1992). The results of these studies seem to indicate that performance depends on the particular variables, models and data used. Using monthly data from a single restaurant, Cranage and Andrew (1992) show that time series models performed as well or better than more complex econometric models. In addition, the performance of many time series models did not improve as its level of complexity increased.

Literature specific to forecasting in the restaurant industry is very limited in terms of the number of studies. Messersmith, Moore, and Hoover (1978) designed a multi-echelon system to generate statistical forecasts of menu-item demand in hospitals in intervals, from one through twenty-eight-days prior to patient meal service. The three interdependent echelons were: (1) forecasting patient census, (2) estimating diet category census, and (3) calculating menu-item demand. Olsen and Jose (1982) used data on two restaurants to compare single and double exponential smoothing models. They find that, while they do generate a delayed reaction, they are effective at identifying long-term trends. Wacker (1985) analyzes the traditional planning problems of the restaurant industry and explains the restaurant planning procedures: forecasting, menu analysis, recipe formation, material requirements planning, capacity requirements planning, and how they are used to derive an effective cost plan. Miller and Shanklin (1988) conducted a survey to assess the forecasting techniques utilized by foodservice directors. This survey was administered to a random sample of 834 American Dietetic Association Members with management responsibilities in the health care delivery system. Forst (2011) used several regression and Box-Jenkins models to forecast weekly sales at a small campus restaurant. For these data, the results indicate that a multiple regression model with two predictors, a dummy variable and sales lagged one week, was the best forecasting model considered. Messersmith and Miller (1992) discussed methods to forecasting quantity and quality demands for menu items. They define what a forecast is; provide essential data for forecasting; tell how to gather data; discuss how to evaluate the data, and discuss how to modify the system to improve results. Yavas (1996) presents a case study on demand forecasting. Morgan *et al.* (1997) builds forecasting models for O'Malley's Restaurant adjusting for the self-selectivity bias where sales are observed only when a restaurant is opened seasonally. Using daily observations of customer counts Hu et. al. (2004) compare six univariate time series and two econometric models to forecast demand at a casino buffet in Las Vegas, Nevada. They find that a double moving average time series model provided the most accurate forecast. As mentioned above, Reynolds et.al. (2013) compare econometric to time series forecasting models. They find that using annualized data, aggregated to the industry level, econometric models provided the most accurate forecasts.

Although accurate, the difficulty of these more complex causal econometric models can be prohibitive for many restaurant managers. Thus, this paper focuses on simple time series forecasting models that can be performed by independent restaurateurs with little statistical expertise using standard spreadsheet software, such as Excel. As such, more advanced topics such as co-integration and non-stationarity are outside of the purview of this paper. A full discussion of these more advanced topics can be found in Green (2001) and Hamilton (1994).

Data

Data for the years 2006-2008 were obtained from Victor's Bistro, a full menu, full service bistro in Florence, South Carolina. Victor's Bistro is an independently owned and operated upscale restaurant that has been in business since 1998, with one location. It is, therefore, classified as a single location, full-service restaurant. In the U.S. in 2008, there were 189,683 restaurants with this classification, with total revenue of 125 billion dollars and consumer spending totaling around 10 trillion dollars (Andy Brennan, 2014). Currently, there are 324 food service and drinking places in the Florence, SC Metropolitan Statistical Area. Of these, 124 are full service restaurants (US Census Bureau, 2011). However, Victor's Bistro has very little direct high-end competition in the Florence area. Chain restaurants, such as Olive Garden, Longhorn Steakhouse, and Red Lobster, compete for diner's dollars, but Victor's Bistro is positioned as superior to these options in food quality, ambiance, and exclusivity.

Because of competition for consumer's food spending, profit margins are generally low for single location, full-service restaurants, and the ability to succeed in this industry is determined by a number of factors, such as "access to multi-skilled and flexible workforce, ability to quickly adopt new technologies, attractive product presentation, proximity to key markets, ability to control stock on hand, and ensuring pricing policy is appropriate" (Andy Brennan, 2014). Victor's is well situated to succeed according to these factors. In addition, this type of restaurant has customers who generally make over $100,000 per year (Andy Brennan, 2014), and Florence, South Carolina is also attractive from this perspective with approximately 16% of the households earning over $100,000 and 27% earning over $75,000 (US Census Bureau, 2010).

Figure 1 shows the number of Victor's customers per month for the years 2006, 2007, and 2008. There has been significant variation from year to year, especially in the later months of each year. For example, beginning in month 11, or November, we see a consistent upward trend, denoting the holiday season. Also, 2008 marks a steady decline until the holiday seasonal bump. This coincides with The Great Recession, when overall consumer spending began to fall. Typically customers view fine dining as a luxury good with higher income elasticities than quick service restaurants (Y. Koh, S. Lee, & C. Choi, 2013). As incomes levels decreased, so did the number of customers each month.

Figure 1: Number of Customers per Month

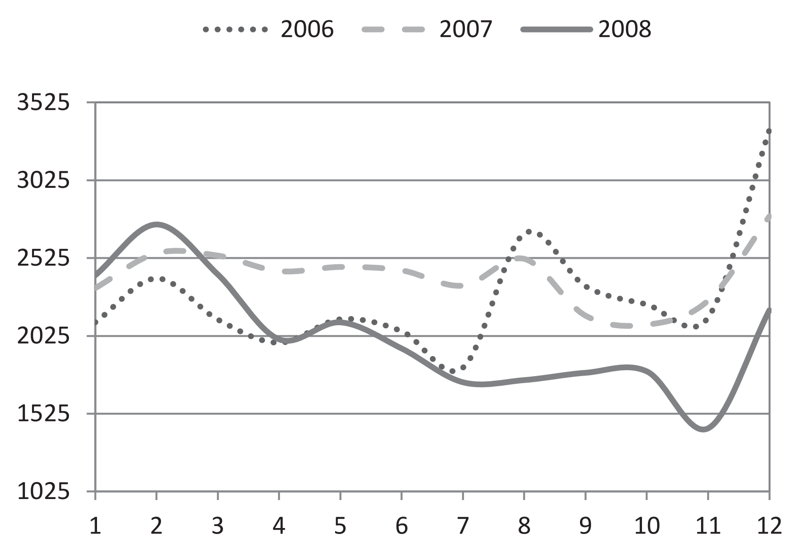


Figure 2 represents the number of tables served per month in the restaurant. While there was strong growth towards the end of 2006, 2007 remained consistent, ending the year with almost exactly the same number of tables served. After a small initial increase at the start of 2008, the restaurant began the downward trend that was apparent in so many areas of the economy. The number of tables served fell steadily throughout most of 2008, with again a seasonal boost towards the end of the year.

Figure 2: Number of Tables per Month

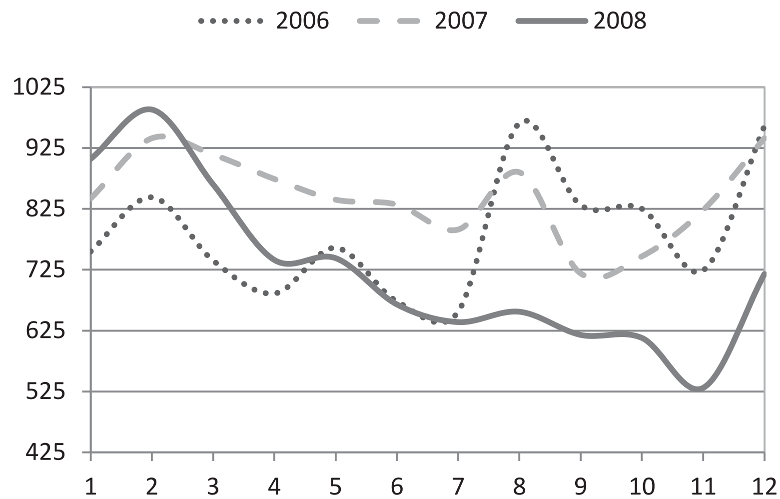


Figure 3 looks at average revenue per customer. With few exceptions, average revenue per customer in 2006 and 2007 was fairly steady. But 2008 brought a significant shift towards an upward trend; seemingly contradictory to intuition since the number of clients and tables both fell.

Figure 3: Average Revenue Per Customer

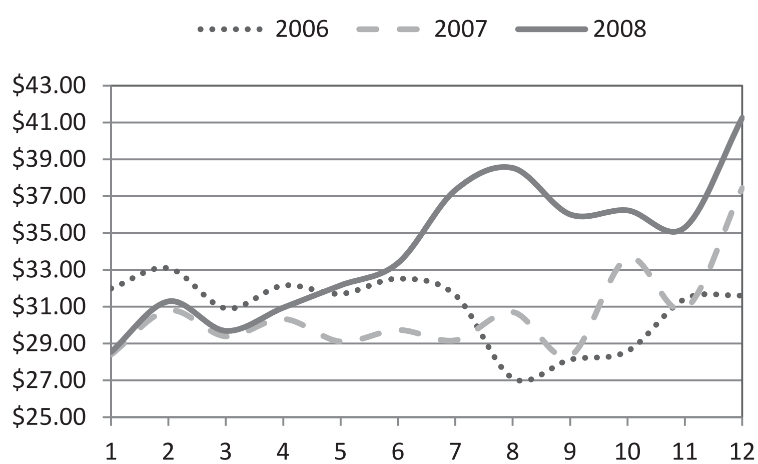
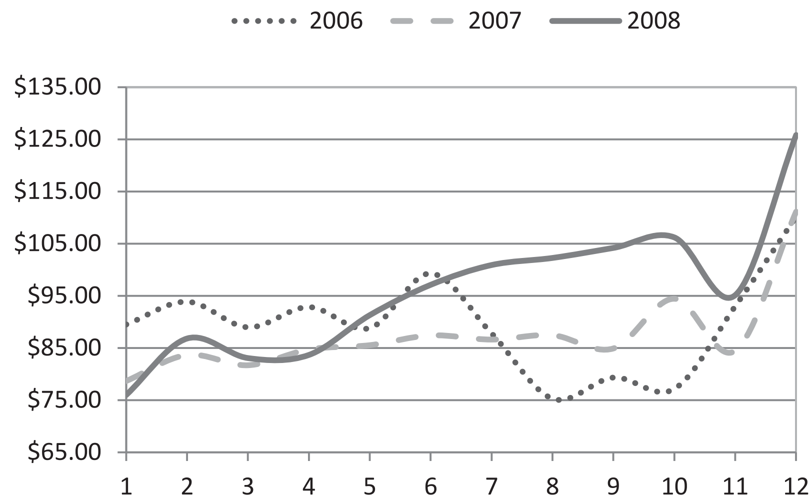


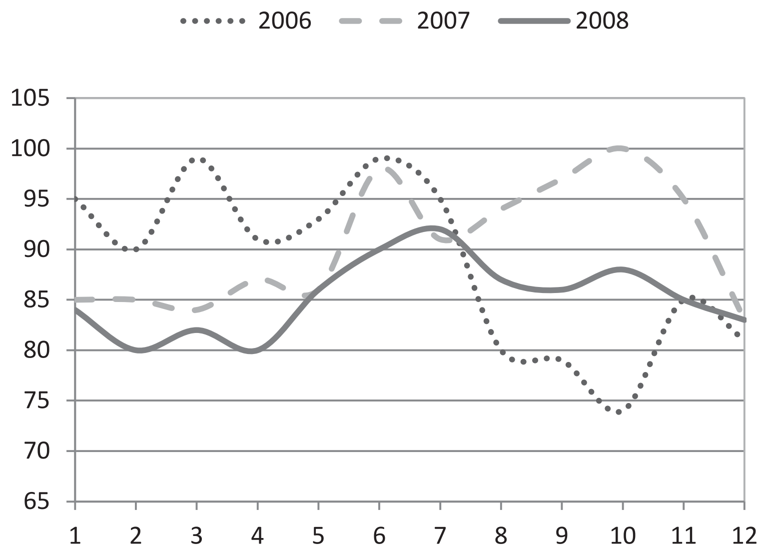
Figure 4 looks at average revenue per table. The data is similar in nature to Figure 3 where we see an increase in revenue per table in 2008. The average revenue per table during 2006 and 2007 is fairly stable.

Figure 4: Average Revenue per Table



Finally, Figure 5 represents table turnover; this is the amount of time a single party occupies a table before the next group of guests is seated. These data show some strong variation between years. While the beginning of 2006 is fairly steady, turnover time drops sharply after the middle of the year. There is some increase in turnover time at the beginning of 2007, with a decrease towards the end of the year. The end of the year decrease could be caused by the increase in the number of clients served due to the holiday rush, forcing the restaurant to encourage faster turnover. The lowest turnover time is in 2008, with a small increase in the summer months.

Figure 5: Table Turnover (in minutes)



Methods

There are a variety of methods which are effective at forecasting long-term variables, such as number of customers and revenues. Basic time-series models, such as exponential smoothing and the Holt-Winter's method, can be useful when simply forecasting based on historical trends and seasonal variability. Given the amount of seasonality in the data, we have chosen three methods (1) Exponential Smoothing, (2) Holt Winters method and (3) Time Series Trend with seasonal indices (a regression model that is adjusted with seasonality). The exponential smoothing method has been chosen as a baseline method, as it does not incorporate changes to due to trend and seasonality, and we can compare how well the other two methods do when seasonality and trend are taken into consideration.

Exponential smoothing is an averaging technique that allows weights to be assigned to past data. The forecast uses a smoothing constant that is estimated based on these weights. However, it is possible to produce sluggish forecasts that do not react quickly to changes in data or forecasts that react too quickly to changes in the data based on the value of the smoothing constant. As a result, these forecasts can often vary considerably, leaving the restaurant owner with a large possible range of values.

Holt-Winter's method incorporates both trend and seasonality. In this method, three constants are estimated: a level, a trend, and a seasonal. However, much like the simpler exponential smoothing method, if the constants are small or large, they can create forecasts that do not react to recent data, or are too reactive.

The last technique utilizes a basic regression equation to create a time series trend coefficient to forecast sales data. We use Excel's Data Analysis Tool Pack to generate the basic regression equation:

$$\hat{Y}_t = b_0 + b_1 t + \epsilon \qquad (7)$$

where t is the time period, b_0 is the intercept, b_1 the slope of the independent variable t, and ϵ is the error term. Once we have the regression equation, we have captured the trend with the slope of the independent variable.

We can then calculate seasonal indices for each time period as the average ratio of actual value to the predicted value for each season. From these seasonal indices for each time period we calculate average seasonal index for each season. The forecast is the linear equation (7) multiplied by the corresponding seasonal index. This gives us an initial starting point for optimization with the decision variables being the intercept (b_0), the slope (b_1) and the seasonal indices for each season. We use Excel's solver to minimize the mean square error by optimizing the decision variables. The only constraint is that the average of the seasonal indices should be equal to 100%. A practical implementation of all three methods can found in Spreadsheet Modeling and Decision Analysis (C.T. Ragsdale, 2008).

Results

We ran the three different forecasting methods based on the three years of data. We evaluated the three methods using the Root Mean Square Error (RSME) for each of the variables to be forecasted. Table 1 gives us the RMSE for the three forecasting methods for each of the variables. Lower RMSE indicates a better forecast.

Table 1: Root Mean Square Error

	Exponential Smoothing	Holt-Winter's Method	Regression adjusted with Seasonality
Number of Clients	2345.48	315.75	246.09
Number of Tables	624.83	92.57	83.53
Average Revenue Per Client ($)	17.33	3.42	2.29
Average Table Per Client ($)	74.33	10.18	6.53
Table Turnover (min)	33.97	8.91	5.42

The exponential smoothing method has the highest error for all the five variables and performs the worst based on this criteria. This is because it is essentially a static forecasting method and does not take into account the seasonality and trend which is present in the data. The Holt-Winter's Method has a smaller error as it does take into account trend and seasonality, but using the simple regression adjusted for seasonality has the lowest error. Each method is progressively more complex than the previous one, and in this case, the most complex method performs the best. Thus, we analyze the forecasting results for each variable using the simple regression method as it has the lowest error across all the five variables.

In order to demonstrate the effectiveness of this technique, as well as its possible disadvantages, we provide two sets of forecasts. The first utilizes 33 of the 36 months of data available to predict the last three months of sales. The second uses only 30 of the 36 months to forecast the last six months of data. Based on these forecasts, we can determine how a restaurant manager could utilize this information and evaluate its accuracy.

Number of Clients

Table 2 gives us the regression model and seasonal indices for the number of clients per month. The slope of the intercept varies for the two forecasts, indicating a possible positive or negative trend. The seasonal indices give us an indication of the months in which demand is more or less than average. For example, in the 3 Month Forecast seasonal indices, demand is 10.80% more in February and 2.38% more in March, but is depressed by 6.94% in April and 2.57% in May. Based on the indices, demand peaks in February and December and is depressed in July. The same trends hold in the 6 Month Forecast seasonal indices.

Table 2: Regression Model with Seasonal Indices for Number of Clients per Month

Intercept	2379.27	2293.28
Slope	-4.889	3.147
Month	3 Month Forecast Seasonal Indices	6 Month Forecast Seasonal Indices
1	98.59%	97.99%
2	110.80%	109.74%
3	102.38%	101.04%
4	93.06%	91.37%
5	97.43%	95.32%
6	93.79%	91.38%
7	85.98%	89.39%
8	101.78%	111.25%
9	92.25%	96.07%
10	94.02%	92.22%
11	95.70%	93.65%
12	134.21%	130.58%

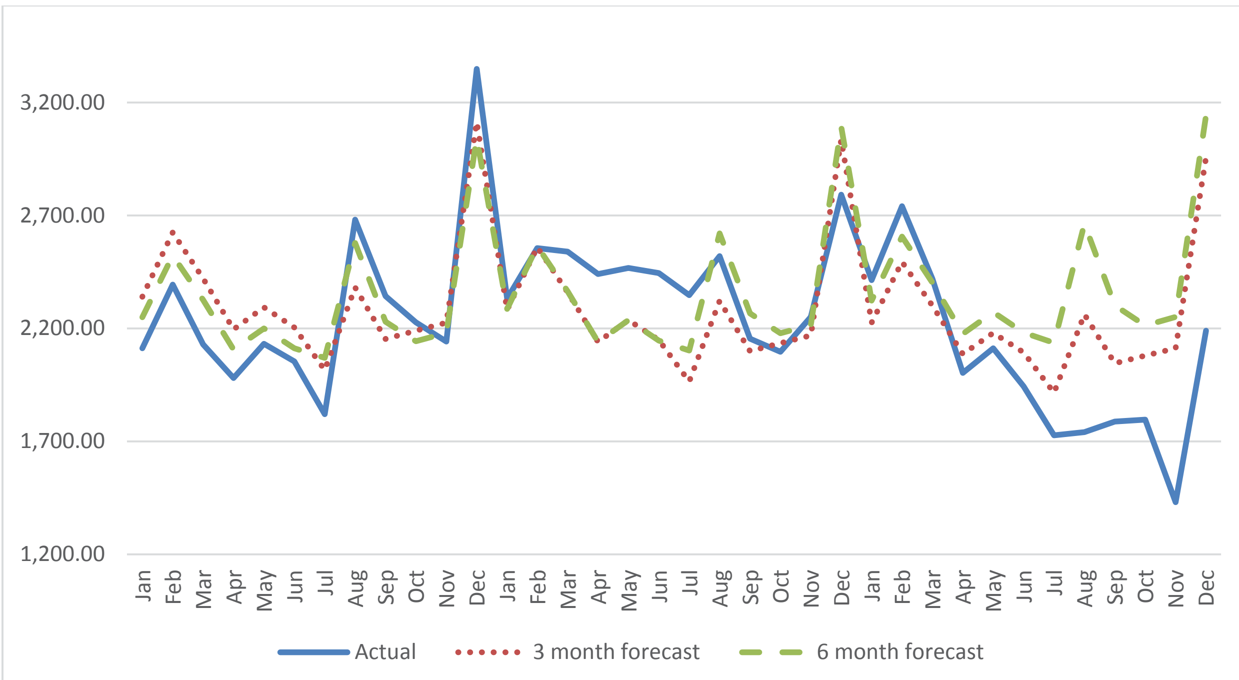
Table 3 presents the seasonal forecasts for the last three and six months of 2008, as compared to the actual values. Both forecasts overestimate the number of clients the restaurant can expect to serve. The three month forecast does a better job of estimating the demand; this result is most likely because the three month forecast includes more data than the six month forecast.

Table 3: Seasonal Forecasts for Number of Clients, 2008

	Actual Number of Clients	3 Month Forecast	6 Month Forecast
July	1727		2137.13
August	1741		2663.20
September	1788		2303.02
October	1797	2080.77	2213.58
November	1431	2113.26	2250.85
December	2190	2956.96	3142.54

Figure 6 graphically illustrates the forecasts across all time periods, based on the regression models. The forecasts appear to follow the patterns of the actual data, but do diverge towards the end of the time period observed. As a restaurant manager, it is important to determine what would cause this anomaly. In this case, it is likely that the early effects of the Great Recession are impacting the restaurants customer demand.

Figure 6: Comparison of Actual and Forecasted Number of Clients, 2006-2008



Number of Tables

Table 4 presents the regression model for the number of tables served per month. Again, in these forecasts, the slope of the intercepts in the forecasts indicate different trend directions. However, the seasonal indices again show peak demand in February and December and depressed demand in July.

Table 4: Regression Model with Seasonal Indices for Number of Tables per Month

Intercept	806.45	779.22
Slope	-0.205	2.449
Month	3 Month Forecast Seasonal Indices	6 Month Forecast Seasonal Indices
1	103.82%	103.05%
2	115.01%	113.74%
3	104.50%	103.00%
4	95.49%	93.72%
5	97.35%	95.12%
6	90.23%	87.90%
7	86.64%	89.33%
8	104.19%	113.64%
9	90.12%	94.83%
10	97.87%	95.92%
11	96.32%	94.31%
12	118.47%	115.45%

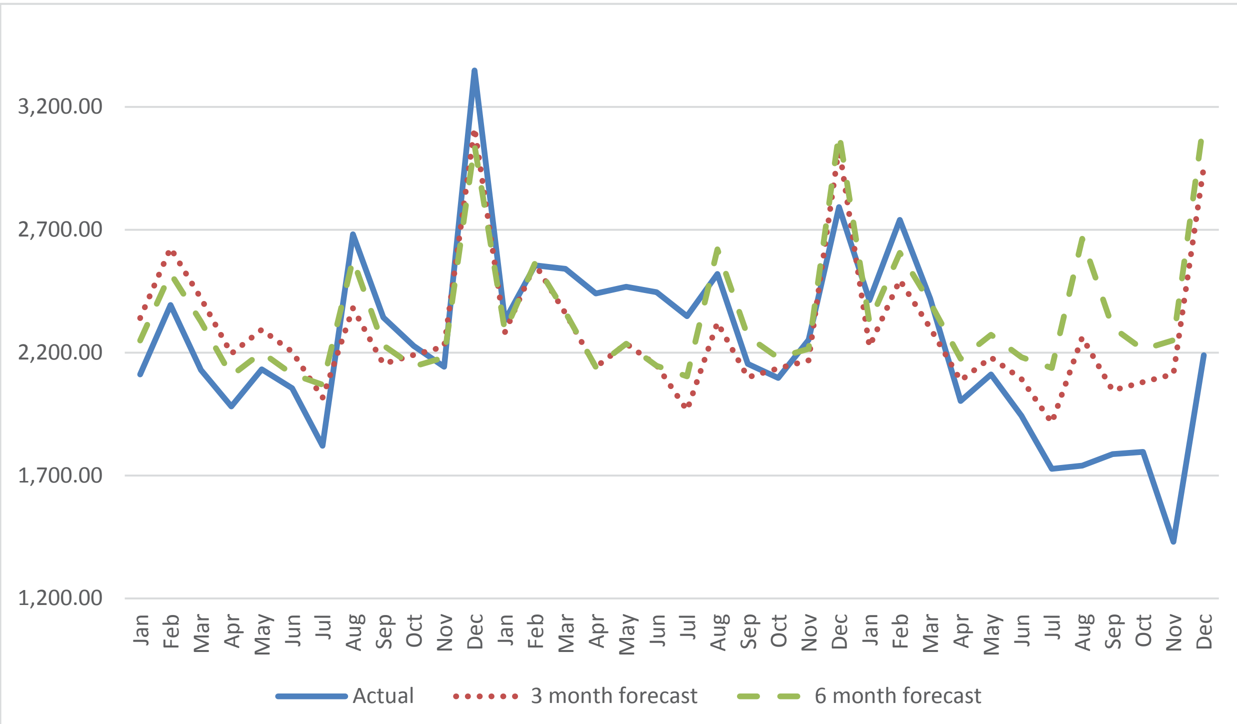
Table 5 shows the three and six month forecasts for 2008. Again, the forecasts overestimate the demand for the number of tables in the restaurant, with the three month forecast creating a more accurate approximation.

Table 5: Seasonal Forecasts for Number of Tables, 2008

	Actual Number of Tables	3 Month Forecast	6 Month Forecast
July	639.00		763.86
August	656.00		974.56
September	618.00		815.54
October	613.00	782.45	827.33
November	531.00	769.87	815.71
December	718.00	946.65	1001.41

Figure 7 graphically illustrates the forecasts. The forecasts seem to reflect the actual values, but again diverge toward the end of 2008, when economic trends would become more significant. That macroeconomic data is not reflected in these forecasts, so while demand began to decrease due to the onset of the recession, these forecasts would not reflect that trend.

Figure 7: Comparison of Actual and Forecasted Number of Tables. 2006-2008



Average Client Revenue

The regression model for average client revenue is presented in Table 6. Along with prior equation estimates, the slopes of the coefficient in the regressions are of opposite signs. There are also some differences in the peak demand periods. In the forecasts for number of clients and tables served, February and December were peak months, and July demand was depressed. Now, while December is still a peak month, July and June are also peak months in the three and six month forecasts, respectively. It is possible that, while the restaurant serves fewer customers in the summer months, the remaining customers spend more money, leading to relatively higher average revenue per client. This is supported by Engel's Law (1857), which states that as income rises, the proportion of income spent on food decreases. In this case, while wealthier customers spend a smaller percentage of their income on food, the absolute level of that spending would be greater. In the case of a recession, wealthier customers are more likely to continue to be able to afford consuming meals outside of the home, increasing the average client revenue.

Table 6: Regression Model with Seasonal Indices for Average Client Revenue

Intercept	29.718	30.820
Slope	0.1039	-0.0006
Month	3 Month Forecast Seasonal Indices	6 Month Forecast Seasonal Indices
1	95.17%	96.22%
2	101.59%	102.97%
3	95.76%	97.36%
4	99.10%	101.09%
5	98.35%	100.59%
6	100.85%	103.47%
7	103.35%	98.68%
8	101.39%	93.85%
9	96.85%	91.62%
10	99.28%	100.99%
11	98.88%	101.11%
12	109.44%	112.06%

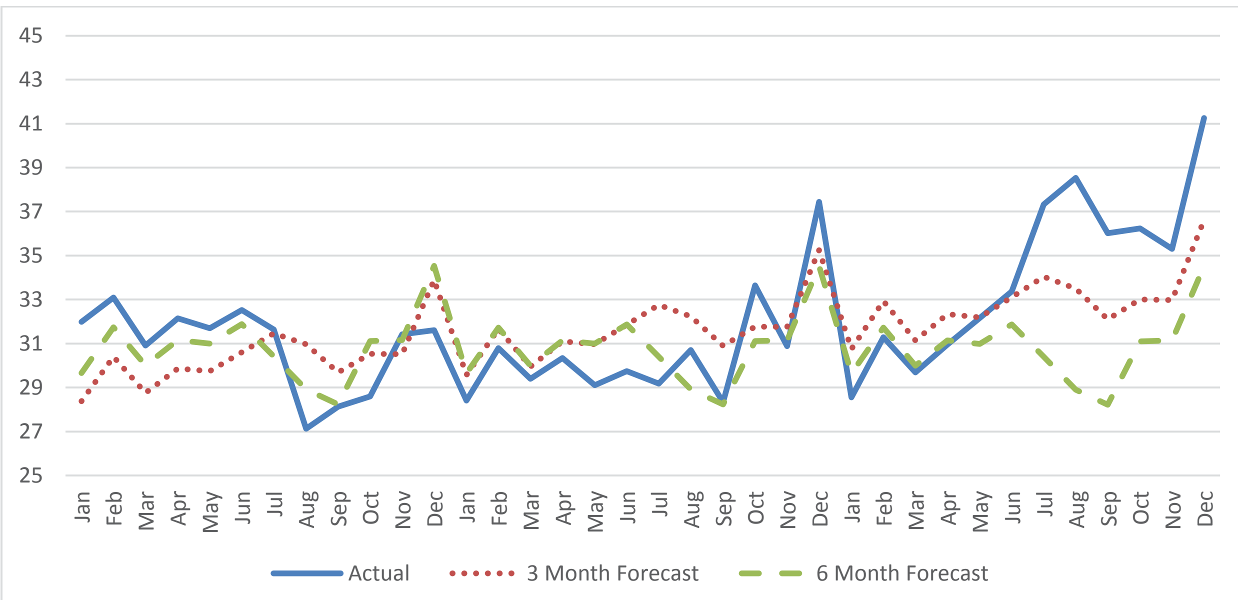
The three and six month forecasts are presented in Table 7 for average client revenue. The average client revenue is now underestimated in both forecasts. In the previous forecasts, we discussed the impact of the Great Recession on the restaurant's demand. Here, as also supported by the seasonal indices, the forecast estimates are lower possibly because, as overall demand has decreased, the customers that continue to patronize the restaurant are spending more. This trend would not be reflected in earlier data that was used to forecast the last three and six months. As a result, it would imply that our forecasts are not as accurate because they do not take into account those macroeconomic variables.

Table 7: Seasonal Forecasts for Average Client Revenue, 2008

	Actual Average Client Revenue	3 Month Forecast	6 Month Forecast
July	37.33		30.394264
August	38.53		28.904436
September	36.01		28.219884
October	36.23	33.01	31.103561
November	35.3	32.98	31.138882
December	41.25	36.61	34.512293

Figure 8 graphically presents the forecasts for average client revenue. It is clear that in 2008, while actual average client revenue rises, the forecasted values do not fully incorporate that trend.

Figure 8: Comparison of Actual and Forecasted Average Client Revenue, 2006-2008



Average Table Revenue

The regression model and seasonal indices for average table revenue are presented in Table 8. The slopes of both forecast coefficients are of opposite signs again for this sales variable. Much like average customer revenue, the peak demand months occur in June, July, and December, with the trough in January. This continues to support the argument that given the beginning of the recession, the remaining restaurants patrons are spending more per person and also per table compared to earlier periods.

Table 8: Regression Model with Seasonal Indices for Average Table Revenue

Intercept	87.312	90.239
Slope	0.153	-0.1212
Month	3 Month Forecast Seasonal Indices	6 Month Forecast Seasonal Indices
1	91.01%	91.86%
2	98.42%	99.55%
3	94.32%	95.68%
4	96.92%	98.66%
5	98.47%	100.39%
6	104.99%	107.43%
7	101.79%	98.36%
8	97.92%	91.84%
9	99.00%	92.85%
10	95.68%	97.09%
11	98.64%	100.67%
12	122.83%	125.63%

Table 9 gives the three and six month forecasts for average table revenue. Again, the forecasted values are lower than the actual values. The restaurant manager would need to consider how the looming recession might be impacting demand, both overall and from the remaining customers.

Table 9: Seasonal Forecasts for Average Table Revenue, 2008

	Actual Average Table Revenue	3 Month Forecast	6 Month Forecast
July	100.9		85.062998
August	102.26		79.310808
September	104.18		80.075703
October	106.2	88.5202	83.609872
November	95.13	91.40447	86.572661
December	125.81	114.0173	107.88745

Figure 9 compares the actual and forecasted values for average table revenue. Despite a wide gap in the forecast in earlier months of 2008, the forecast toward the end of 2008 seems to be more accurate. This is most likely explained by customers who spend more money during special occasion restaurant experiences during holiday months that are seen every year during the time periods analyzed.

Figure 9: Comparison of Actual and Forecasted Average Table Revenue, 2006-2008

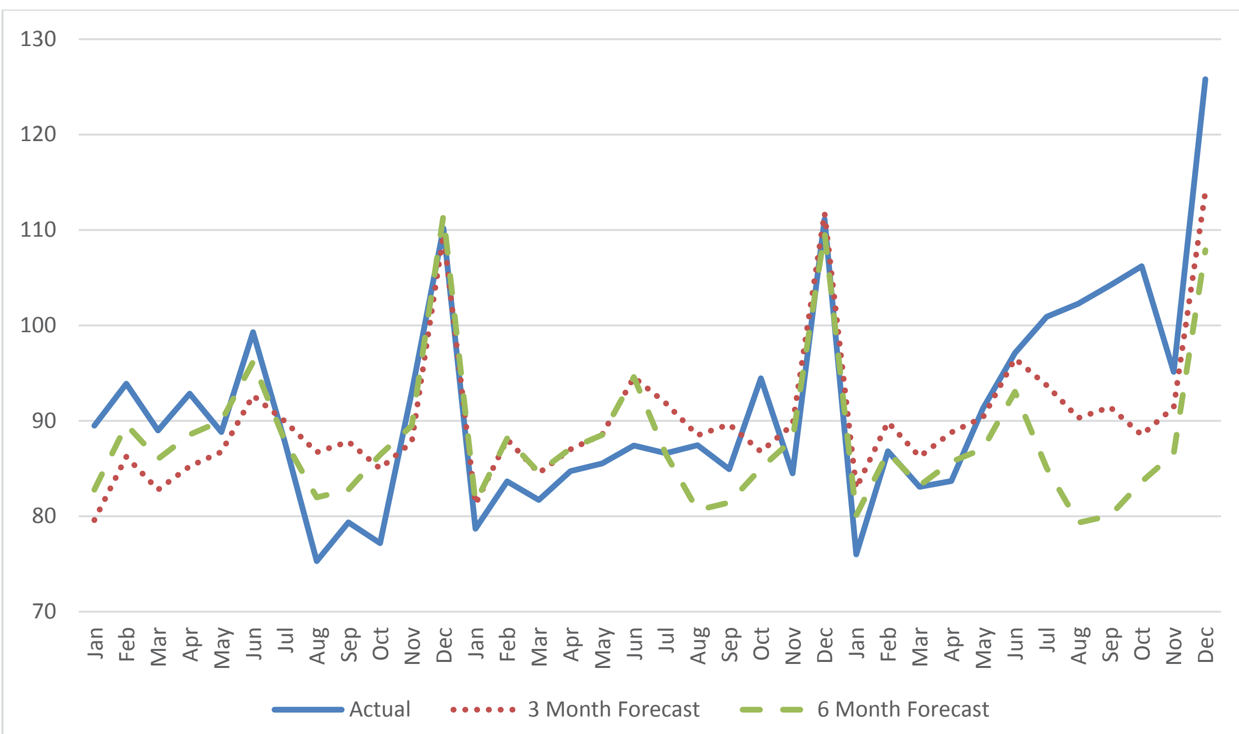


Table Turnover

Table 10 presents the regression model and seasonal indices for table turnover in the restaurant, in minutes. Both forecasts have similar intercepts and coefficient slopes. Additionally, the peak summer months of June and July now contrast to the faster turnover times in December. Patrons spend on average a longer amount of time in the summer months as compared to special holiday meals in December. An overall lower demand, from customers and for tables, could be the reason for this trend. For example, given the large influx of customers in the holiday month of December, the restaurant may find it profitable to increase turnover to allow more customers in the restaurant in a given night to help satisfy demand.

Table 10: Regression Model with Seasonal Indices for Table Turnover

Intercept	90.64	90.96
Slope	-0.1489	-0.1794
Month	3 Month Forecast Seasonal Indices	6 Month Forecast Seasonal Indices
1	99.26%	99.35%
2	96.04%	96.15%
3	100.02%	100.19%
4	97.50%	97.69%
5	100.28%	100.50%
6	108.80%	109.08%
7	105.52%	104.94%
8	99.16%	98.25%
9	99.71%	99.55%
10	98.42%	98.57%
11	102.08%	102.29%
12	93.20%	93.44%

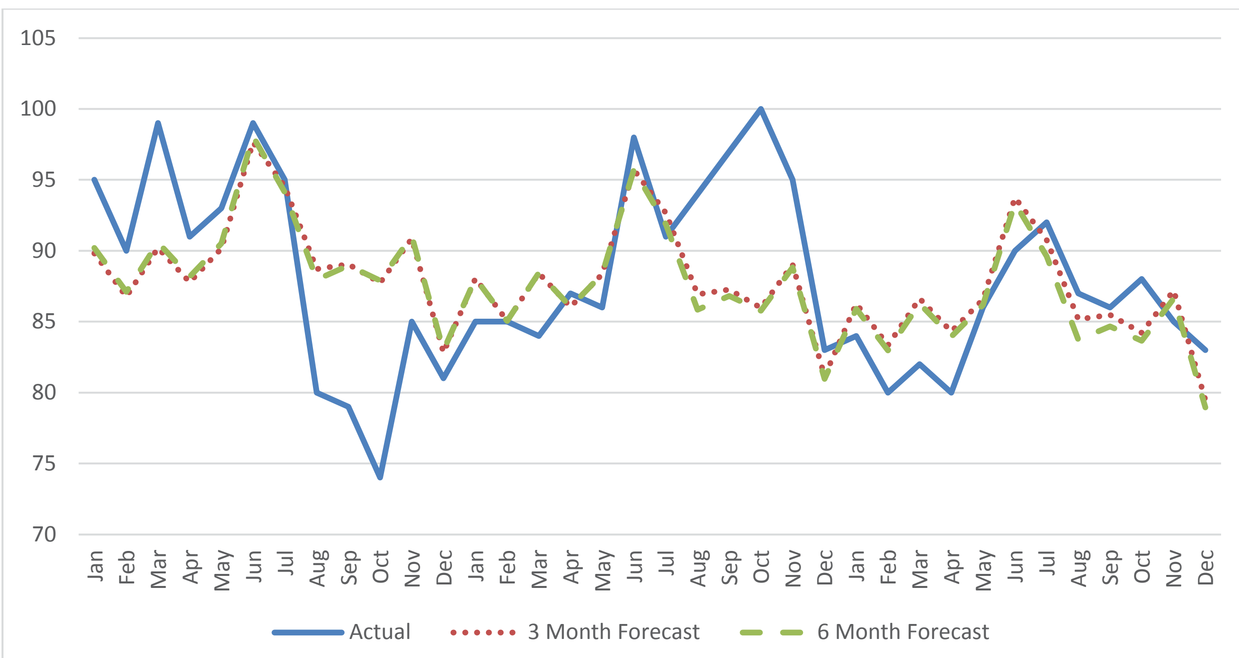
Table 11 shows the forecasts for table turnover. Again, both forecasts slightly underestimate the actual values, but remain close to those times. Despite higher average spending per customer and table, patrons are not spending a significantly longer period of time at the restaurant.

Table 11: Seasonal Forecasts for Table Turnover, 2008

	Actual Table Turnover	3 Month Forecast	6 Month Forecast
July	92		89.62
August	87		83.73
September	86		84.66
October	88	84.22	83.65
November	85	87.20	86.62
December	83	79.48	78.96

Figure 10 compares the actual and forecasted values graphically. Interestingly, the last months of 2008 offer some of the best predictions of table turnover times. The graph shows that while the forecasts certainly show more moderate fluctuations, actual values can vary considerably, especially in late summer and early fall months.

Figure 10: Comparison of Actual and Forecasted Table Turnover, 2006-2008



Discussion and Implications

Using a basic time series trend regression with seasonal indices, we were able to estimate and three and six month forecast for a restaurant. Although the forecasts did not perfectly reflect the actual data, they do offer value to restaurant managers attempting to determine future demand in three ways.

First, the time series forecasts here are based on a short time period of observation. This is certainly a limitation of the forecasts presented. However, many restaurant managers have access to multiple years of data that they can use to forecast future demand. Although we have only three years here, these models can easily be extended to as many years of data as the manager has available. In each of the forecasts for our demand variables, we found that the 3 month forecast was consistently more accurate than the 6 month forecast, simply by virtue of more data. As more data is included, the forecasts will more accurately reflect seasonal trends and give a better look toward the future.

Second, while these forecasts do provide a sense of the direction of demand, they did not accurately reflect all the factors that change demand. For this particular data set, the onset of the Great Recession would have a significant impact on the accuracy of the forecast. If a restaurant manager based their decisions only on the time series forecasts, this would lead to errors. In combination with macroeconomic developments of the economy, however, the forecast can be very useful at predicting what could be expected. For example, if the forecast normally predicts December as a month with increased demand, as these models do, a large and abnormal rise in unemployment rates in October and November of that year should lead the restaurant manager to reevaluate that estimate.

Finally, forecasting techniques, even ones that are complex and include a variety of macroeconomic variables, will never predict demand without some amount of error. Thus, the restaurant manager must also consider their own expertise and knowledge when interpreting the accuracy of the forecasts. A manager with years of experience may tend to lean on judgmental forecasts because of past experience. However, what our results show is that these time series models create a good foundation for the predictions of future demand, which in combination with a manager's experience will help successfully lead the business in the future.

Conclusion

In this paper, we have shown how time series forecasting can be a useful tool for small business owners to predict future revenues and demand. We have shown that small business owners can use these relatively simpler time series models with just their sales data. Comparing three different time series models, it was evident the time series trend regression with seasonal indices had the lowest error. We then analyzed the results using the best model and showed that there were varying trends in the different forecasts with respect to the different variables. As discussed, the onset of the Great Recession likely had a large impact on the accuracy of these forecasts, which provided a good example of the importance of considering exogenous macroeconomic indicators in combination with our models.

These kinds of insights can give a small business owner a competitive advantage in planning for demand for the next year. The drawback in time series models is that it assumes that the past patterns repeat themselves and may not be as robust as more complex econometric models, especially when there are events which are not embedded in the past data. However, they are simple to use and a step up from most judgment models that many restaurant owners currently use. These time series models use the restaurant's data and could validate the restaurant owner's judgement and show them that their "hunch" or instinct was right or could show how their judgement was flawed and help them re-evaluate their assumptions.

These forecasting models can then be used as inputs into the sales and operations plans for these restaurants, allowing them to plan for staffing, inventory, and other operations, which are required to meet the fluctuating demand. Future research could look at comparisons between time series and econometric/causal models to see if models containing additional information would be superior to pure time series models. But it is important to note that restaurant managers must also consider macroeconomic conditions when evaluating these forecasts, to ensure that a large exogenous variable may reduce their accuracy. Thus, using these time series models in combination with the restaurant manager's experience and observations can mean highly accurate and useful forecasts.

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