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Tips Predict Restaurant Sales

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Abstract

An analysis of seven years of monthly charge-card sales and tip data from a multi-regional restaurant chain in the United States found that tip percentages predicted food sales in the following month. Thus, restaurant executives, managers, and owners are encouraged to add tip percentages to their sales forecasting models.

Keywords

sales forecasting, tipping, tip percentage

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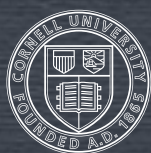
Hospitality Leadership Through Learning

Tips Predict Restaurant Sales

by Michael Lynn, Ph.D.
and Andrey Ukhov, Ph.D.

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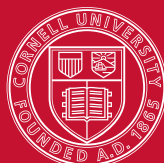
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Tips Predict Restaurant Sales

by Michael Lynn and Andrey D. Ukhov

EXECUTIVE SUMMARY

An analysis of seven years of monthly charge-card sales and tip data from a multi-regional restaurant chain in the United States found that tip percentages predicted food sales in the following month. Thus, restaurant executives, managers, and owners are encouraged to add tip percentages to their sales forecasting models.

ABOUT THE AUTHORS

Michael Lynn, Ph.D., the Burton M. Sack '61 Professor in Food and Beverage Management, is a professor of consumer behavior and marketing at the Cornell University School of Hotel Administration. He received his Ph.D. in Social Psychology from the Ohio State University in 1987, and has taught in the marketing departments of business and hospitality schools since 1988. His experience of paying his way through school by waiting tables and bartending sparked his interest in service gratuities (tipping), a topic on which he has over 50 published academic papers. His other research focuses on consumer status and brand differentiation. A former editor of the *Cornell Hospitality Quarterly*, Lynn is an associate editor of the *Journal of Socio-Economics* and an editorial board member for the *Journal of Hospitality and Tourism Research* and the *International Journal of Hospitality Management.*

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Tips Predict Restaurant Sales

by Michael Lynn and Andrey D. Ukhov

Sales forecasts are a critical tool at all levels of the restaurant industry. Restaurant managers use sales forecasts to better estimate the amounts of food, beverages, and other supplies they must order and to more efficiently schedule employees to cover labor needs. Restaurant owners and restaurant chain executives use sales forecasts to secure loans, to woo potential investors, to inform their own reinvestment decisions, and to set benchmarks against which their unit managers' performances are measured and rewarded. Given the considerable applied interest in restaurant sales forecasts at both the unit and corporate level, many restaurant firms employ sophisticated statistical techniques to generate such forecasts.[1]

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[1] For example, see: Y.N. Green and P.A. Weaver, Approaches, techniques and information technology systems in the restaurants and food-service industry: A qualitative study in sales forecasting. *International Journal of Hospitality and Tourism Administration*, 9, No. 2 (2008), 164-191)

A modest body of research has addressed restaurant industry sales forecasting. Several studies have shown that restaurant sales can be predicted from sales in prior periods or trends over time.[2] Furthermore, researchers have found that restaurant sales prediction can be improved by adding such factors as day of week, month of year, holidays, weather, and (for casino restaurants) showroom headcounts to models that include previous period sales or temporal trends.[3]

This paper contributes to the restaurant sales forecasting literature by examining the predictive utility of another variable readily available to restaurant managers and executives—namely, charge-card tip percentages. Tips might predict future sales for at least two reasons. First, current service levels affect current tips and intentions to return.[4] To the extent that repeat patronage intentions affect future sales, then current tips may predict future sales because they serve as a proxy for current service quality, which drives future sales. Second, as voluntary payments whose amounts are determined by consumers after services have been received, tips are arguably the most discretionary of consumer expenditures. As such, it is plausible that changes in economic conditions and the resulting consumer sentiment affect tips before they affect other less discretionary expenditures. If so, then tips may be a leading indicator of consumer sentiment. Since consumer sentiment affects future retail sales or sales growth,[5] tip information that reflects consumer sentiment should predict future restaurant sales. These ideas that tip amounts may reflect two drivers of future sales—current service levels and consumer sentiment about the economy—suggest that adding tips to forecasting

models may improve the prediction of restaurant sales. We test this possibility in a novel data set as described next.

Method

A large, multi-regional restaurant chain provided daily sales and tip information for ten restaurants, which are scattered across the United States. The data are from February 2005 through January 2012, a time period which includes both periods of economic expansion and contraction. This chain has substantial non-food revenues that are not customarily accompanied by tipping, so data were provided about the charge-card tips and sales coming from revenue centers that are typically tipped, as well as gross and net revenues across all revenue centers. Our data comprised the following:

(1) TIPS—charge-card tips from those revenue centers where tips are common (hereafter referred to as "selected revenue centers"),

(2) TOTAL SALES A—charge sales from selected revenue centers (excluding split checks with more than one payment method and charges with no charge tip),

(3) TOTAL SALES B—charge sales from selected revenue centers (excluding any charges from split checks with more than one payment method),

(4) GROSS REVENUE—total sales from all revenue centers and all payment methods minus inclusive taxes, and

(5) NET REVENUE—total sales from all revenue centers and all payment methods minus discounts and inclusive taxes.

We aggregated the data across units and days to get aggregate monthly charge sales and tips from those charge receipts that included a tip. Then we divided aggregate tips by aggregate sales to calculate monthly tip percentages (PERCENT TIP). We used only charge receipts with a non-zero tip to generate PERCENT TIP because many people leave cash tips even when paying for their meal with a credit card and including their charge sales in the denominator of PERCENT TIP would have biased that measure.

Results and Discussion

Exhibit 1 lists summary statistics for the data series. We aggregated all data for the ten units to obtain aggregate monthly data. The minimum percentage tip in our data is 16.65 percent, and the maximum is 18.62 percent. We would like to point out that this range in monthly tip percentages of about 2 percent of sales provides enough variability to justify looking at the predictive power of PERCENT TIP. Exhibit 2 displays a plot of total sales (TOTAL SALES A), TOTAL TIPS (left vertical axis) and PERCENT TIP (right vertical axis) and illustrates variation in the data.

[2] D. Cranage, Practical time series forecasting for the hospitality manager. *International Journal of Contemporary Hospitality Management*, 15, No. 2 (2003), 86-93; D.A. Cranage and W.P. Andrew, A comparison of time series and econometric models for forecasting restaurant sales. *International Journal of Hospitality Management*, 11, No. 2 (1992), 129-142; M.M. Davis and P.D. Berger, Sales forecasting in a retail service environment. *Journal of Business Forecasting Methods and Systems*, 7, No. 4, (1988/1989), pp. 8-11; F.G. Forst, Forecasting restaurant sales using multiple regression and Box-Jenkins analysis. *Journal of Applied Business Research*, 8, No. 2 (1992), 15-19; M.S. Morgan and P.K. Chintagunta, Forecasting restaurant sales using self-selectivity models. *Journal of Retailing and Consumer Service*, 4, No. 2 (1997), 117-128; and E. Suh and J.J. West, Estimating the impact of entertainment on the restaurant revenues of a Las Vegas hotel casino: An exploratory study. *International Journal of Hospitality Management*, 29 (2010), 570-575.

[3] Davis and Berger, *op.cit.*; Morgan and Chintagunta, *op.cit*; and Suh and West, *op.cit.*

[4] M. Lynn, Tip levels and service: An update, extension, and reconciliation. *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 44, No. 5–6 (October 2003), pp. 139-148; and S. Jang and Y. Namkung, Perceived quality, emotions, and behavioral intentions: Application of an extended Mehrabian-Russell model to restaurants. *Journal of Business Research*, 62 (2009), pp. 451-460.

[5] T.A. Garrett, R. Hernandez-Murillo and M.T. Owyang, Does consumer sentiment predict regional consumption? *Federal Reserve Bank of St. Louis Review*, 87, No. 2, Part 1 (2004), 123-135.

EXHIBIT 1

Total sales, gross revenue, and tip percentages

	Total Sales A	Total Sales B	Gross Revenue	Net Revenue	Percent Tip
Mean	$2,209,662	$2,928,348	$11,545,457	$10,936,937	17.657%
Median	$2,223,437	$2,922,936	$11,636,143	$11,007,021	17.612%
Standard Deviation	$260,606	$344,357	$1,695,897	$1,678,298	0.545%
Minimum	$1,768,954	$2,306,851	$8,518,506	$8,004,205	16.656%
Maximum	$2,869,594	$3,754,777	$17,117,084	$16,583,584	18.624%
Autocorrelation	0.366	0.345	0.164	0.195	0.935

EXHIBIT 2

Variation over time in total sales, total tips, and percent tip
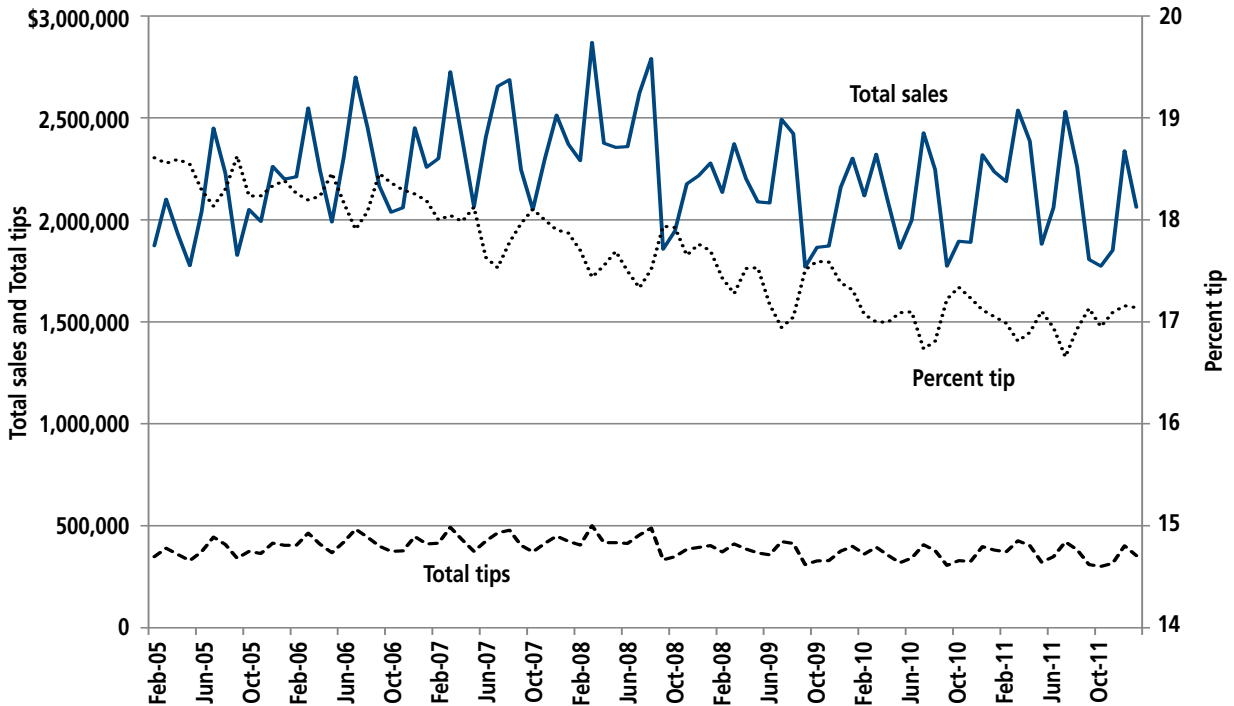
We assessed the predictive utility of PERCENT TIP using regression analyses. However, time series data like those we are using typically violates assumptions about the independence of error terms that underlie statistical tests, and this can make the p-values from those tests invalid. This problem, known as serial correlation in the data, can be addressed by controlling for values of the dependent and independent variables from previous time periods. Those measures from previous time periods are known as lagged values. Therefore, we included lagged values of the dependent and independent variables in our regression models in order to control

for serial correlation in our data. Our regression models also controlled for linear and curvilinear (quadratic) trends in sales over time as well as for monthly differences in sales. We ran four regression models—one for each of the dependent variables: TOTAL SALES A, TOTAL SALES B, GROSS REVENUE, and NET REVENUE (see Exhibits 3 and 4).

In regressions predicting TOTAL SALES A and TOTAL SALES B, the coefficients for PERCENT TIP lagged by one month (that is, PERCENT TIP from the previous month) were positive and statistically significant. This means, for instance, that when tip percentage in the prior month is higher than

Exhibit 3

Regression results of tip percentages as a predictor for monthly food sales

	Total Sales A	Total Sales B
Constant	-195,048	-468,833
	(-0.07)	(-0.13)
Trend	6,884.90	7806
	(1.44)	(1.23)
Trend Squared	-73.99	-70.42
	(-2.29)**	(-1.71)*
Total Sales A (-1)	0.47	
	(4.55)***	
Total Sales B (-1)		0.4662
		(4.57)***
Percent Tip (-1)	**366,835.49**	**476,866.63**
	(2.58)***	(2.47)**
Percent Tip (-2)	-284,023.20	-353,36.95
	(-1.93)*	(-1.78)*
Monthly Dummies	Included	Included
Durbin-Watson	2.22	2.25
R-squared	0.84	0.83

Note: Significance levels as follows: * $p < .10$, ** $p < .05$, *** $p < .01$

tip percentage two months previous, then TOTAL SALES from the current month tend to be higher than TOTAL SALES from the prior month. In this case, a one-point increase in PERCENT TIP (e.g., from 14 to 15 percent) predicted a $366,835.49 increase in TOTAL SALES A the following month and a $476,866.63 increase in TOTAL SALES B in that following month across all ten units studied. Thus, it appears that tips do predict sales from the revenue centers that generated the tips.[6]

_____

[6] We also estimate a regression model that includes all the other explanatory variables (lagged sales, linear and quadratic time trends, and monthly dummy variables), but omits lagged tips. The model without tips explains 81% of the variation in TOTAL SALES A, leaving 19% of the variation unexplained, and it explains 79.7% of the variation in TOTAL SALES B, leaving 20.3% of the variation unexplained. When tips are added to the model, the information contained in the tips helps explain 15% of the unexplained variation in the case of TOTAL SALES A, and 15.3% of the unexplained variation in the case of TOTAL SALES B.

In additional tests, we also examine whether the coefficient on percent tip is the same for a tip increase as for a tip decrease. To do this, we define

In regressions predicting GROSS REVENUE and NET REVENUE, the coefficient for PERCENT TIP lagged by one month was positive, but only marginally significant. A one-point increase in PERCENT TIP (e.g., from 14 to 15 percent) predicts a $1,366,592.94 increase in GROSS SALES the following month across the ten units studied and a $1,201,243.25 increase in

a dummy variable that takes the value of 1 in a month when PERCENT TIP is higher relative to the prior month, and takes the value of 0 otherwise. The variable is TIPS INCREASE. We estimate additional regressions, where we include TIPS INCREASE to account for potentially different intercepts between tips increase and tips decrease; we also include the interaction variables, (Tips Increase)*(Percent Tip(-1)), and (Tips Increase)*(Percent Tip(-2)), to account for potentially different effect of Percent Tip on sales for tip increase and tip decrease. First, our main results continue to hold: An increase in Percent Tip (-1), our main variable of interest, remains statistically significant, so an increase in PERCENT TIP forecasts an increase in sales. Second, the coefficient for the interaction term, (Tips Increase)* Percent Tip (-1), is positive and marginally statistically significant for both the TOTAL SALES A and the TOTAL SALES B regressions (in the Total sales A regression the *t*-statistic is 1.71, and in the Total sales B regression the *t*-statistic is 1.73, $p < .10$ in both instances). This indicates that increasing tips may have a stronger effect on sales than do decreasing tips.

Exhibit 4

Regression results of tip percentages and sales of non-food items

	Gross Revenue	Net Revenue
Constant	20,242,971	19,300,400
	(1.21)	(1.20)
Trend	1,756	-40
	(0.06)	(-0.00)
Trend Squared	-272.5	-276.2
	(-1.57)	(-1.64)
Gross Revenue (-1)	0.2677	
	(2.33)**	
Net Revenue (-1)		0.2709
		(2.36)**
Percent Tip (-1)	**1,366,592.94**	**1,201,243.25**
	(1.58)[a]	(1.44)[b]
Percent Tip (-2)	-1,761,714.86	-1,570,952.10
	(-2.00)**	(-1.85)*
Monthly Dummies	Included	Included
Durbin-Watson	2.01	2.02
R-squared	0.86	0.87

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$; [a] one-tailed *p*-value is 0.06; [b] one-tailed *p*-value is 0.08.

NET SALES the following month across all ten units studied.[7] These effects did not reach the conventional level of statistical significance, but neither one would occur by chance more than eight times out of 100. Thus, we feel comfortable concluding that tips also predict sales from all revenue centers, but that conclusion should be regarded as tentative pending future replications.[8]

[7] We also estimate a regression model that includes all the other explanatory variables (lagged revenues, linear and quadratic time trends, and monthly dummy variables), but does not include lagged tips. The model without tips explains 84.8% of the variation in GROSS REVENUE, leaving 15.2% of the variation unexplained, and it explains 85.7% of the variation in NET REVENUE, leaving 14.3% of the variation unexplained. When tips are added to the model, the information contained in the tips helps explain 7.9% of the unexplained variation in the case of GROSS REVENUE, and 7.7% of the unexplained variation in the case of NET REVENUE.

[8] In additional tests, we also examine whether the coefficient on percent tip the same for a tip increase as for a tip decrease. Using the same

Conclusions

An analysis of seven years of monthly sales and tip data from a multi-regional restaurant chain in the United States found that tip percentage reliably predicted related sales in the following month. The precise relationship between charge tips and future sales will vary across restaurant chains and even across specific restaurants, so our findings cannot be directly used to forecast your sales. Our results are useful, however, in providing evidence that charge tips can predict sales. Thus, we encourage other restaurants and restaurant chains to add charge tips to their forecasting models. ■

methodology as in footnote 6, we again found our main results continue to hold: An increase in PERCENT TIP (-1) is marginally statistically significant, so an increase in PERCENT TIP forecasts an increase in revenue, but the coefficient for the interaction termwas not statistically significant Thus, we are unable to conclude that increasing tips and decreasing tips have different effects on sales from all revenue centers.

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