International Journal of Economics, Commerce and Management
United Kingdom Vol. VI, Issue 7, July 2018
http://ijecm.co.uk/ ISSN 2348 0386

EXPENDITURE BARRIERS IN INDIVIDUAL MEAL RESTAURANT ORDERING

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Abstract

Price points are an important consideration in the analysis of optimal pricing. We contribute to this literature by proposing that consumers have total expenditure barriers when purchasing a bundle of items from a seller. We suggest a rationale for, and test the proposition that, individuals set reservation expenditure levels for meal purchases using salient points in multiples of $5. We test this hypothesis using a sample of online orders from 257 restaurants clustered into five restaurant types. Single meal orders were identified by removing transactions having more than one entrée leaving 52,583 transactions for individual level analysis. Orders were analyzed by Payment Type (cash versus credit) × Meal Category (weekday lunch, weekday dinner, weekend lunch, weekend dinner) for each restaurant cluster. Two distributions are examined, final ticket amount and proportion of individuals with a particular base cost that added an additional item of $3 or less to the order. The data demonstrate that final ticket *amounts peak just below a multiple of $5 and order adding behavior is greater just above than just below a multiple of $5. Both distributions exhibit strong evidence of expenditure barrier purchasing for dinner purchases and mixed evidence of such purchasing for lunch purchases.*

Keywords: Online ordering, Focal points, Price points, Psychological pricing

JEL codes: M5

INTRODUCTION

Extensive research has examined psychological pricing. Thomas and Morwitz (2005), for example, examine the use of just under pricing and develop the cognitive rationale for why a nine ending price is considered cheaper than a price one cent higher ($9.99 versus $10.00). They argue that people consider $9.99 to be in the $9 range and therefore cheaper than $10. Put another way, consumers round prices rather than view them holistically (Liang & Kanetkar, 2006). Kreul (1982) argues that such numbers can stimulate sales even relative to lower-priced round numbers. He also argues that consumers have a tendency “toward rounding, or viewing a whole range of prices in terms of one magic number” (p. 75). Parsa and Naipaul (2007) argues that, in the restaurant context, fine-dining restaurant managers deliberately use the price ending 00 as a pre-purchase signal to emphasize the quality orientation of their products and quick-service restaurant managers use the price ending 99 to signal the value orientation of their products. Such pricing information is especially important in an online environment because purchasers are precluded from using certain attributes (e.g. aroma) in an online setting (Wagner & Jamsawang, 2014). A related literature, particularly relevant to our study, examines the overrepresentation of 0 and 5 as ending prices (Schindler & Kirby, 1997; Stiving & Winer, 1997).

Kreul (1982) argued for the existence of menu price barriers for entrées that differ by segment ($1 for fast food, $10 for casual dining). Twenty five years later, Ruggless (2007) noted that casual dining entrées have broken the $20 price barrier. (It is worth noting that both of the casual dining entrée barriers they discuss are multiples of $5.) We contend that consumers create similar barriers for their overall meal order.

We extend the broad literature on the psychology of consumer pricing and spending behavior by proposing that consumers buying a bundle of goods gravitate towards expenditure barrier points. That is, when consumers buy multiple products or services from a single seller, they spend an amount that gravitates towards certain salient numbers. The obvious numbers end in multiples of 5 for both practical, and instinctive, reasons.

The denomination of currency provides an important practical spur toward barrier behavior in this instance, especially for customers who are paying with cash. The expressions “can you break a five” (or ten or twenty) and “keep the change” are part of our lexicon and signal the qualitative difference between smaller and larger denomination bills. It is worth noting that this same tendency does not exist with regard to the $2 bill, which, while still a circulating denomination of U. S. currency, is of sufficient rarity that the U. S. Department of Treasury has to dispel rumors that it has removed the $2 bill from circulation (Treasury, 2007). As a result, the barriers examined in this paper are multiples of $5.

The outcomes examined in this study, the total amount of money spent by an individual when ordering food online from a restaurant, is the result of individual action rather than two-party negotiated interaction. The individual’s decision calculus in creating an order is based on reacting to posted data (menu prices as well as ancillary charges) rather than on negotiation over those charges. This decision involves intra-agent action, not inter-agent interaction of the kind discussed by Schelling (1960).

As such, this situation is similar to the analysis of individual stopping points for physical activity performances like sit-ups and push-ups that can only be performed in integer quantities (Erfle & Gelbaugh, 2013; Erfle, 2014). They found that individuals achieved endings in multiples of 5 more often than random processes would suggest. This situation is also akin to age heaping, the phenomenon in survey research in which individuals round up or down one’s self-reported age to the nearest multiple of 5 (A'Hearn, Baten, & Crayen, 2009). The central premise of this paper is that individual ordering behavior possesses this same gravitation toward numerically simplistic solutions, at least for a significant portion of consumer transactions.

Erfle (2014) argues that this gravitation toward numerically simplistic solutions for individual behavior has roots in early childhood. Five appears to be a particularly easy counting ending for a variety of reasons. Finger patterns play is important in developing arithmetic skills (Marton, 1992). Children initially use fingers to count, but “finger counting goes even farther, as it allows the children to infer the base-10 mathematical system” (Andres, Di Luca, & Pesenti, 2008, p. 642). Skip counting by 2 and 5 employs five or two 1s digit solutions (2, 4, 6, 8, 0 and 5, 0), respectively. By contrast, skip counting by all other single digit numbers employs all 10 digits prior to 1s digit pattern repetition. This may explain why the error rate for multiplication by five is lower than other operands (Baroody, 1985; Mulligan & Mitchelmore, 1997) and why the average response time for single digit multiplication by five is even faster than multiplication by two (Campbell & Graham, 1985). Children are taught to count using tally marks in groups of five to facilitate accurate counting. The fifth tally mark crosses the other four and can be viewed as the hand with the thumb folded (Marton, 1992).

We are interested in modeling typical behavior as opposed to special occasion behavior. Our working hypothesis is that individuals have routines and that one of those routines is to set reservation prices on meal purchases. A reservation price is the upper bound on the amount of money that an individual is willing to pay for a good or service. In the context of a meal purchase, the individual is typically considering the purchase of a bundle of items (entrée, appetizer, drink) from a restaurant. Each item under consideration will have its own reservation price (which must exceed the price charged by the restaurant for that item to remain under consideration), but the meal itself is also likely to have a reservation expenditure. We contend that more individuals will have meal reservation expenditures at salient outcomes than at non-salient outcomes. (We believe that more people have a decision rule [reservation expenditure] which says "I don't want to spend more than $10" or "I don't want to spend more than $15," than "I don't want to spend more than $12" on a meal.) We do not believe that these barriers are sharply defined for most consumers. For example, a consumer who has a meal reservation expenditure barrier at $10 would likely consider a total bill of $10.34 as a satisfactory outcome (unless the consumer was paying with cash and faced the constraint of only having a $10 bill) but is less likely to view $11.34 in the same fashion. This view is consistent with the notion of price rounding as discussed by Kreul (1982).

If individuals set expenditure barriers in multiples of $5, then we will be able to observe evidence of this behavior in online ordering information and if it is not true, then the patterns that emerge may provide us with alternative behavioral explanations for the observed ordering behavior. Our initial expectation is that barrier behavior will be more apparent in cash transactions than credit transactions. We also expect it to be more apparent when an individual orders a single meal than when the individual orders for a group. As a result, we restrict our analysis to single meal purchases and we separately examine cash and credit transactions.

The present research focuses on the total expenditure of an online restaurant order. We believe that more people have a total cost constraint (reservation expenditure for the meal) at expenditure points of $10, $15 and $20 than at surrounding dollar amounts. These outcomes provide natural bounds for what a person is willing to spend on a meal. If this is true, then an individual may be more likely to add items until reaching these expenditure points, or stop right before these expenditure points. For instance, a $9 purchase and a $7 + $2 purchase are likely purchases according to our proposed salient expenditure purchase behavior.

RESEARCH METHODS

MenuDrive is an e-commerce platform marketed to restaurants in the U.S. that was founded in 2006. The company uses a business-to-business model, selling a web-based online ordering system targeted at individual restaurants as opposed to franchise restaurant chains. While the company uses a unified system to support its various clients, the system possesses a large degree of flexibility, providing a customizable web-based graphical user interface for different restaurants. MenuDrive and GrubHub are competing online restaurant ordering companies. GrubHub is a directory portal that allows the user to input an address and choose from a list of nearby participating restaurants. People can sort through restaurants based on the restaurant's popularity and food type. Then, the customer can choose one restaurant and order items from that restaurant's menu. MenuDrive's business model does not allow customers to access nearby participating restaurants but instead, each restaurant is treated as a separate entity with its own website. The customer goes directly to that restaurant's URL to see their menu and can order items without knowing that they are using the MenuDrive ordering system. The online store, Shopify, provides a service for general retailers similar to MenuDrive's service for restaurants.

After they complete their selections, customers confirm their orders by electing to pay online (credit) or offline (cash). Information from the transaction is sent to the restaurant and the transaction data is stored in the MenuDrive database. Since its inception, MenuDrive has accumulated a significant amount of transactional data from a variety of restaurant types and geographical locations in the US.

The subset of the MenuDrive dataset used in this study spanned the time-period from May 2009 to May 2013, having a total value of more than $11.4 million. The transactional data includes the type and number of items purchased, the method of payment (cash or credit), the order type (delivery or takeout), and the local time of the order. The restaurant information includes the name of the establishment and its address.

Clustering Restaurants

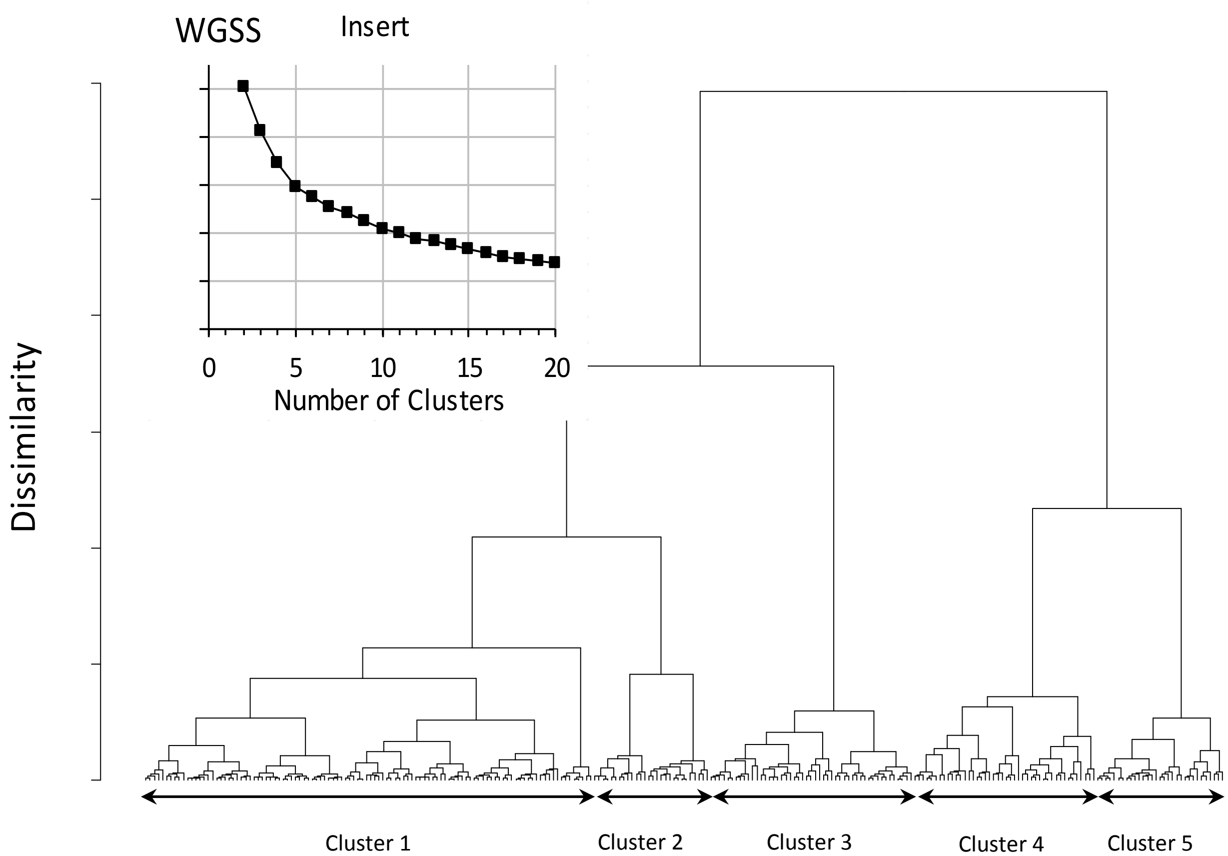
Because the MenuDrive dataset comes from a large variety of restaurants encompassing different geographic locations, socio-economic environments, and restaurant types, we elected to first examine the set of restaurants to determine if there was an internal structure to this dataset before continuing with the transaction-level analysis. To winnow out individual spending behavior against the backdrop of this variability, we elected to cluster the restaurants into similar groups prior to analyzing the individual transaction data. We examined several variables available in the dataset to describe the salient features of a particular restaurant in order to survey for internal structure in the dataset. Our intent was to create groupings in which the restaurants in a particular cluster are more likely to possess clientele who would exhibit similar purchasing behavior patterns.

Prior to performing the restaurant clustering, several data preprocessing steps were completed. First, we removed restaurants with fewer than 100 transactions (these clients used the system in a trial fashion). We also removed all restaurants specializing in event catering because we wish to examine individual ordering behavior. A total of 260 restaurants remained in the dataset after this preprocessing.

We used six variables to classify restaurants: expense index (describing how expensive a restaurant is in its neighborhood), delivery rate (percent of orders using delivery), credit rate (percent of orders using credit), discount rate (percent of orders using a discount), lunch rate (percent of orders before 3:00 pm), and weekend rate (percent of orders between Friday 3:00 pm and Sunday 11:59 pm). These six variables describe each restaurant's macro-level information and aggregated customer transactions information. The expense index was designed to capture the "local-affordability" of the restaurant. To calculate the index, we determined the average income for the restaurant's ZIP code using data from the 2000 Census. This value was normalized by dividing it by the average income over all regions. This normalized value was used to scale the average menu price at the restaurant, calculated using a 20% trimmed mean of prices for all items in the menu. This index provides a compact measure of the restaurant's cost relative to local income. These six variables were then standardized to be centered with unit variance. Using these standardized variables (z scores) for clustering, we expect the clientele within a particular restaurant cluster to exhibit similar consumer behavior.

The restaurant clustering process was performed using a hierarchical clustering algorithm implemented in R version 2.14.1 (R Core Team, 2013). We used the Euclidean distance between the six standardized variables described above to calculate the dissimilarity measure and Ward's method for selecting the clusters to merge at each stage(Ward, 1963). The clustering process can be visualized using the dendrogram in Figure 1.

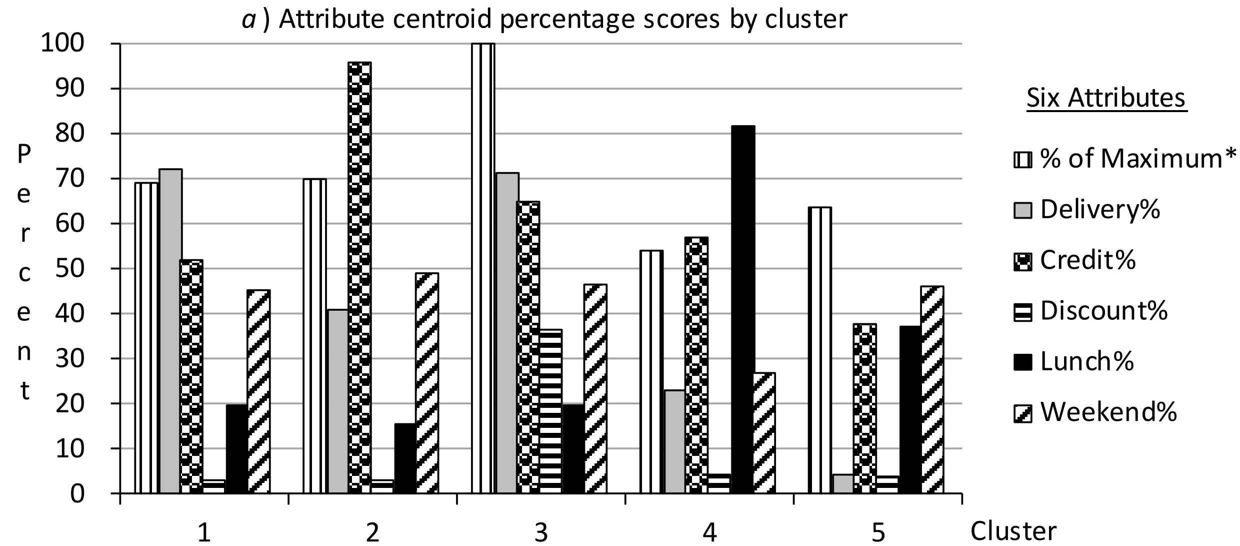
Figure 1. Restaurant Clustering Dendrogram



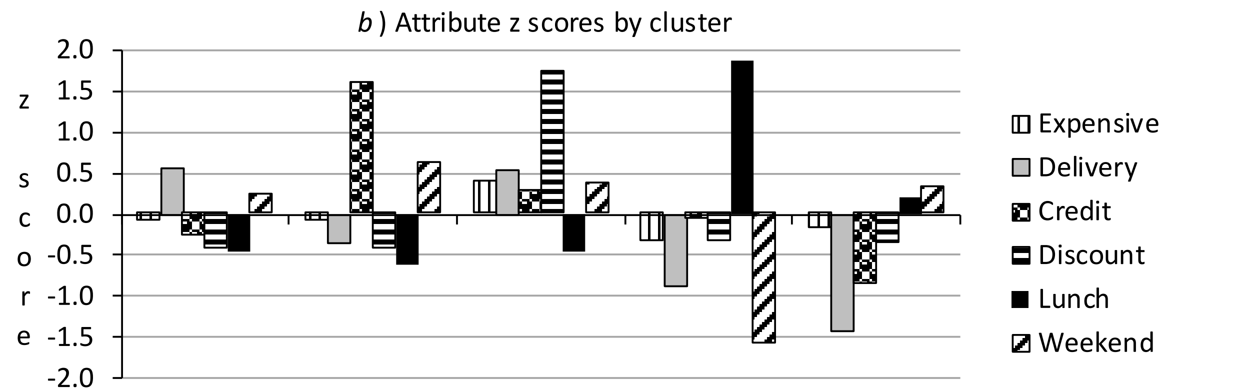
We examined several measures for determining the appropriate number of clusters for the restaurant analysis. Visual examination of the dendrogram suggested between three and eight clusters. We narrowed this range by monitoring the rate of decrease of the within group sum of squares (WGSS). The resulting graph appears as an insert to Figure 1. This function appears to have an elbow at five clusters where the slope changes markedly. Based on this result, we selected five clusters of restaurants for final analysis.

Summary statistics for the five clusters are shown in Figure 2. Each of the six variables is shown in percentage format in panel a and in z score format in panel b. The variable measuring the expensiveness of the restaurant is depicted as a percent of $11.42, the most expensive centroid dollar value (making the expense index for Cluster 3 equal to 100%). The largest, Cluster 1, contained 108 restaurants and has mean z scores for all six attributes below 0.6 in magnitude. We labeled this the Typical cluster. Each of the other four clusters displayed one or more defining features that separated it from other clusters (each defining feature z score was more than 2.5 times the magnitude of 0.55, the largest z score in the Typical cluster). For example, Cluster 4 contained 44 restaurants that displayed a higher fraction of lunch transactions and a low weekend transaction rate, we labeled this the Weekday and Lunch cluster. Note that the clustering process was based on macro-level restaurant information and aggregated transactional information. After classifying the restaurants into these five clusters, the analysis moved to the transactional level where we expected divergent consumer behavior between the clusters since the groups likely represented different customer bases.

Figure 2. Attributes used to Define Restaurant Clusters



* % of Maximum = ([20% trimmed mean of menu items]/[zip code relative income])/$11.12. Zip code relative income = (zip code average income)/(national average income) from the 2000 Census and $11.12 is the centroid dollar value of (20% trimmed mean)/(zip code relative income) for the most expensive cluster.



1	2	3	4	5	Cluster
108	28	49	44	31	*N* restaurants
152,630	35,635	142,310	33,528	15,529	*N* transactions
Typical (Delivery 72%)	Credit (96%) & Dinner (84%)	Expensive & Discount (36%)	Weekday (73%) & Lunch (82%)	Takeout (96%) & Cash (62%)	Defining feature(s) of the cluster
0.34	0.61	0.63	0.85	0.56	Centroid Average |z|

We examined the nature of the clusters prior to analyzing the individual orders. Because meal selection is an interaction between the consumer and the menu set by the restaurant, an analysis performed on a small group of restaurants is likely to reveal mostly menu-driven patterns. To mitigate potential endogeneity in the analysis, we wanted to ensure that no group of restaurants dominated the orders analyzed within any cluster, i.e. we wished to examine purchasing behavior in responding to restaurant prices in general rather than prices of a specific dominant restaurant. We analyzed each cluster using the Herfindahl-Hirschman Index (HHI equals the sum of squared shares for each cluster), a widely used measure of market concentration. According to federal merger guidelines, a market is considered unconcentrated if HHI is less than 1,000 (Justice Department & Federal Trade Commission, 1997). Two of the clusters initially displayed a large HHI, HHICluster2 = 1,602 and HHICluster3 = 957. Further examination revealed one restaurant in Cluster 2 had 35.7% of transactions and two restaurants in Cluster 3 (both pizza restaurants in Chicago owned by the same person) had 37.3%. We removed these three establishments from the analysis and considered the remaining 257 restaurants. The resulting HHI indices were 280, 787, 590, 773, and 750, for Clusters 1-5 respectively, indicating individual restaurant dominance should not be an issue in any cluster. Note that if the two removed Chicago pizza restaurants were considered as one (a reasonable assumption given that both are owned by the same individual), then HHICluster3 = 1,649.

Individual Ordering

The customer transaction data was then analyzed separately for each of the five clusters. We included only customers who were registered users on the portal, because a visitor to the site may not be familiar with the cost structure of the restaurant and may neglect to take into account additional fees, e.g. delivery costs, during the ordering process. A more experienced user is less likely to overlook these costs, which may push an inexperienced user past a barrier point and potentially mask the person's actual intent. Additionally, we elected to filter out group-orders from the analysis because group ordering, such as business lunch orders, dating, or eating with friends and family is likely to have a different and more complex psychology than individual ordering.

To eliminate orders that were likely placed by a group rather than an individual we designed an algorithm to identify these orders. We considered orders containing more than one entrée as a group-order, recognizing that a small fraction of these would have been placed by an individual for personal consumption. Because of the complexity of the menu structure across the 257 restaurants, we used the item price to define an item as an entrée. Specifically, a price threshold was calculated separately for each restaurant and any item priced higher than this value was classified as an entrée. To determine the price threshold for a particular restaurant, we calculated the cumulative distribution function of the menu prices and scanned this distribution for the largest jump over the price range from \$5 to \$9 using increments of \$0.10. We defined the threshold to be the floor of this \$0.10 jump. We removed all the orders containing more than one item priced higher than this threshold value and classified the remaining orders as individual. Finally, we employed a text-mining algorithm to eliminate orders containing a medium or large pizza, as these are classified as entrées but are also likely to represent orders involving more than one individual.

Proportion of Individuals Adding Items at Base Cost Bin y, k(y)

For the purpose of identifying potential expenditure barrier points in individual ordering behavior, we elected to search the orders for psychological expenditure values that represented obstacles to additional expenditure. For example, if \$10 represents an important psychological value for total expenditure, individuals who are already spending \$6 or \$7 may be more willing to add an item costing between \$2 and \$3, while an individual who is already spending \$8 or \$9 may be less willing to do so. We also recognized that this behavior may exhibit different characteristics when the individual is in a lunch or dinner situation, in a weekday or weekend situation, and when using cash or credit.

We defined the base cost for each transaction as the total bill less the price of the least costly item of \$3.00 or less for transactions with more than one item. For transactions with a single item, the base cost is the total cost of the transaction. Base cost values are placed in \$1.00 wide bins based on the integer portion of the base cost (so that values from \$9.00 to \$9.99 are listed in the \$9 bin). Suppose a transaction has three items: a \$3.99 salad, a \$2.99 appetizer, and a \$1.99 drink with a \$1.50 delivery charge and the tax rate is 4%. The base cost for this transaction would be \$8 (8 is the integer portion of \$8.90 = (\$3.99 + \$2.99 + \$1.99 + \$1.50)•1.04 – \$1.99) and this transaction would be listed as having an additional item added.

To analyze individual ordering behavior over a range of prices, we elected to estimate the probability an individual adds an item to their order given the base cost of the order is at a particular price bin y, k(y) = P(Additional item is ordered | Base cost bin = y). This probability should provide information on the willingness of an individual to increase the total cost of an order given the base cost is a particular value and patterns in k(y) could reveal psychological trends in spending habits. To estimate this probability at a base price level y we calculated the proportion of individual orders at that base cost in which the individual added an additional item. We examined these proportions over the base cost bin range from $5 to $20 for individual orders in each of the five restaurant clusters described above and plotted the results to look for trends in base cost spending levels at which people were more or less willing to add items.

Our expectation is that k(y) should be smaller just below each barrier (multiple of 5) and larger just above each barrier. In particular, k1,2Above represents the portion of individuals in base cost bins with remainder 1 or 2 when divided by 5 that order additional items (bins 6, 7, 11, 12, 16, or 17). An individual order in these bins will be described as just above. Similarly, k1,2Below represents the portion of individuals in base cost bins with remainder 3 or 4 when divided by 5 that order additional items (bins 8, 9, 13, 14, 18, or 19). An individual order in these bins will be described as just below. We expect that k1,2Above should exceed k1,2Below. At a purely mathematical level, we could have included those individuals in base cost remainder 0 bin when divided by 5 as being just above (because all but those whose fractional component of base cost was $.00 would technically be above the barrier outcome). We refrained from doing so because our expectation is that many individuals would not view outcomes with this degree of precision. Instead, many would view a $10.37 meal as a $10 meal.

Data Presentation

The results are presented in one figure and four tables. Each of the tables highlights various aspects of the information presented in Figure 3. Table 1 depicts just above versus just below k behavior across the entire spectrum of base cost bins from $6 to $19 for individual meal categories. Table 2 aggregates across meal categories and compares the visual portrayal of additional item adding behavior to the actual record of that behavior across the entire spectrum from $6 to $19. Table 3 focuses on just above versus just below k behavior at specific expenditure barriers and Table 4 examines k behavior between expenditure barriers.

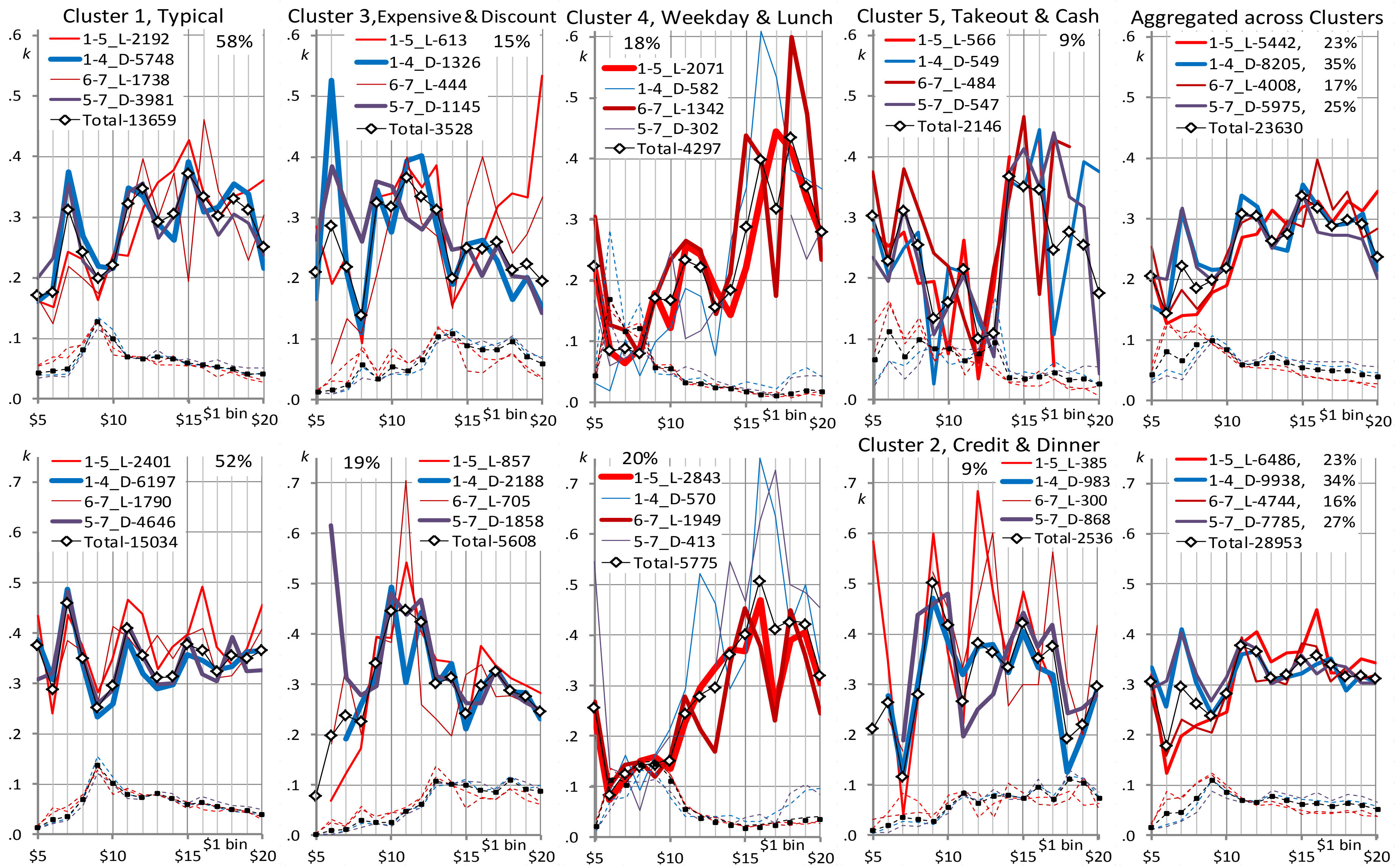
Figure 3 depicts the proportion of orders adding an additional item by base cost bin, k, for Cash (top row) and Credit (bottom row). Separate panels are provided for Cash and Credit for Clusters 1, 3 and 4. The Cash panel for Cluster 2 and the Credit panel for Cluster 5 are omitted due to thin data in these panels. Each panel depicts four meal categories based on time of day and day of the week. Weekday lunch (Monday (1) through Friday (5) before 3:00 pm, labelled 1-5_L) is in red, weekend lunch (Saturday and Sunday before 3:00 pm, 6-7_L) is in maroon. Weekday dinner (Monday through Thursday after 3:00 pm, 1-4_D) is in blue and weekend dinner (Friday through Sunday after 3:00 pm, 5-7_D) is in purple.

Two distributions are shown for each meal category –dashed lines depict the proportion of category orders ending in this final dollar bin and solid line depicts k, the proportion of base cost bin receipts in this category that order an additional item. The weight of each solid k line is proportional to the number of receipts in this category. Total (aggregates the four meal categories for each Cluster × Payment Type) is shown in black for both distributions with larger hollow diamond markers (◊) and solid lines for k and with smaller black square markers (■) and dashed lines for the proportion of orders ending in this final dollar bin. Meal category k(y) values are suppressed if the base cost dollar bin y for this meal category has 10 or fewer transactions, and base cost bins with k = 0 used the Wilson adjustment (Agresti & Coull, 1998). Percent of payment type receipts by cluster are provided at the top of the first four panels. The final panel aggregates across clusters for this payment type and is therefore based on all restaurants viewed together. This panel provides percent of total Cash or Credit in each of the four categories.

Table 1 provides an alternative method for examining just above and just below k(y) behavior to the presentation in Figure 3. This table tests whether the portion of individuals adding orders is significantly different just above than just below a multiple of $5 bins for 32 comparisons (4 Meal Categories × 4 Clusters × 2 Payment Types). The final four columns for each payment type aggregates across clusters for each of the four meal categories.

Table 2 summarizes the general trend and barrier purchasing results from Figure 3 and Table 1 by Cluster × Payment Type. Three aggregated portions are included to the right; the first two mirror Figure 3 and Table 1; the final aggregates these aggregates across payment types. The upper portion of each half provides summary statistics for k portrayed by the 16 ◊k values in each panel of Figure 3. These statistics include mean and slope coefficient for the general trend across base cost bins as well as information on whether this trend is statistically significant and serially correlated. The lower portion of each half of Table 2 provides an individual meal ordering summary by Cluster × Payment Type. It is worth noting that mean ◊k (from the upper half) and actual k (from the lower half) are consistent with one another except for Cluster 4. In this instance, the actual k is substantially lower than that portrayed visually via the Cluster 4 panels of Figure 3 because the vast majority of actual receipts in this cluster are in lower dollar bins (recall this is the heavy lunch cluster) and these bins have lower k values than higher dollar bins. This portion of Table 2 also examines whether there are significant differences between just above and just below k proportions. These proportions aggregate across meal categories of the just above and just below values from Table 1.

Figure 3. Proportion of categories ordering an additional item, k, × $1 bins from $5 to $20 × Cluster × Payment Type (Cash [top], Credit [bottom])



Note: Category acronyms: Day of week # 1 = Mon. to 7 = Sun. _ L = lunch, D = dinner – *N* receipts. Solid lines denote proportion of base cost bin receipts ordering an additional item (for $N_{\text{category bin}}$> 10); dashed lines are the proportion of category orders in this final dollar bin. Solid line weights are proportional to total receipts for this payment type.

Table 1. Proportion of Individuals Ordering Additional Item, k, for Just Above Multiples of 5 with Just Below Multiples of 5 by Meal Category × Cluster × Payment Type

		Cluster 1, *Typical*				Cluster 3, *Discount & Expensive*				Cluster 4, *Weekday & Lunch*				Cluster 5, *Takeout & Cash*				Aggregated Across Clusters			
	Meal Category	1-5L	1-4D	6-7L	5-7D	1-5L	1-4D	6-7L	5-7D	1-5L	1-4D	6-7L	5-7D	1-5L	1-4D	6-7L	5-7D	1-5L	1-4D	6-7L	5-7D
Cash	$M\ \$$ final receipt	11.36	12.03	11.42	12.49	13.17	14.49	12.74	14.53	8.84	9.88	9.18	10.72	9.47	12.00	10.01	12.22	10.38	12.28	10.61	12.77
	$N_{\text{AI 1,2Above}}$	195	565	196	393	62	127	42	104	111	39	99	9	59	45	52	47	427	776	389	553
	$N_{\text{Total 1,2Above}}$	764	1,782	674	1,242	202	409	152	397	958	300	652	128	257	210	220	189	2,181	2,701	1,698	1,956
	$N_{\text{AI 3,4Below}}$	241	690	173	439	75	134	42	129	105	30	70	19	32	44	41	47	453	898	326	634
	$N_{\text{Total 3,4Below}}$	916	2,555	709	1,744	275	633	204	507	713	190	435	113	165	245	147	237	2,069	3,623	1,495	2,601
	$k_{\text{1,2Above}}$	.266	.288	.265	.292	.299	.264	.282	.250	.135	.143	.190	.111	.209	.240	.261	.232	.196	.287	.229	.283
	$k_{\text{3,4Below}}$	.263	.270	.244	.252	.267	.220	.215	.252	.147	.158	.161	.168	.194	.180	.279	.198	.219	.248	.218	.244
	z of $k_{\text{Above}} - k_{\text{Below}}$	0.12	1.25	0.90	**2.41**	0.76	1.61	1.49	-0.07	-0.71	-0.47	1.28	-1.38	0.38	1.62	-0.38	0.84	-1.86	**3.52**	0.75	**2.97**
	p value	.905	.213	.371	**.016**	.445	.108	.137	.948	.478	.641	.201	.168	.705	.105	.701	.401	.062	**<.001**	.456	**.003**
														Cluster 2, *Credit & Dinner*							
Credit	$M\ \$$ final receipt	12.08	12.33	12.15	12.97	14.01	15.29	14.14	15.39	10.05	12.35	10.00	12.45	13.17	14.76	13.49	14.96	11.50	13.21	11.64	13.74
	$N_{\text{AI 1,2Above}}$	347	709	246	544	123	247	87	235	178	76	124	42	43	111	35	81	691	1,143	492	902
	$N_{\text{Total 1,2Above}}$	840	1,938	681	1,489	332	742	241	647	1,099	199	721	132	138	349	99	270	2,409	3,228	1,742	2,538
	$N_{\text{AI 3,4Below}}$	363	834	253	675	114	304	87	246	257	75	155	54	49	110	41	120	783	1,323	536	1,095
	$N_{\text{Total 3,4Below}}$	1,097	2,879	772	2,177	366	1,012	347	839	1,232	275	836	182	151	410	130	396	2,846	4,576	2,085	3,594
	$k_{\text{1,2Above}}$	.403	.344	.375	.350	.347	.353	.380	.353	.174	.342	.190	.338	.355	.330	.347	.337	.287	.354	.282	.355
	$k_{\text{3,4Below}}$	.331	.290	.328	.310	.304	.293	.336	.315	.209	.273	.185	.297	.325	.268	.315	.303	.275	.289	.257	.305
	z of $k_{\text{Above}} - k_{\text{Below}}$	**3.28**	**3.98**	1.90	**2.52**	1.20	**2.68**	1.15	1.57	**-2.11**	1.61	0.21	0.78	0.55	1.86	0.50	0.93	0.94	**6.08**	1.76	**4.17**
	p value	**.001**	**<.001**	.057	**.012**	.230	**.007**	.250	.116	**.034**	.108	.831	.437	.582	.063	.614	.350	.346	**<.001**	.078	**<.001**

Note. Meal category acronymns: Day of week # 1 = Mon. to 7 = Sun. L = lunch, D = dinner. AI = Adding items. $k = N_{\text{AI}}/N_{\text{Total}}$. Just above values have remainder 1, or 2 when divided by 5 (Base cost bins 6, 7, 11, 12, 16, or 17) and are denoted 1,2Above. Just below values, denoted 1,2Below, have remainder 3 or 4 when divided by 5 (bins 8, 9, 13, 14, 18, or 19). All significance level p values based on 2-tailed test with boldfaced values when $p < .05$.

Table 2. Summary Statistics of Correlation between Proportion of Individuals Ordering Additional Item, K, with Base Cost Dollar Bin and Proportion of Individuals Ordering Additional Item for Just Above Multiples of 5 with Just Below Multiples of 5 by Cluster × Payment Type

Cash		Cluster 1, *Typical*	Cluster 3, *Discount & Expensive*	Cluster 4, *Weekday & Lunch*	Cluster 5, *Takeout & Cash*	Aggregated	Aggregated Cash & Credit
16 ◊*k* values from Figure 3	M	.280	.256	.230	.239	.255	.283
	$\Delta k/\Delta$Base cost $ bin	**0.008**	-0.002	**0.018**	0.001	**0.008**	**0.008**
	Durbin-Watson	1.34	1.30	1.41	1.21	1.23	1.34
	$r_{k,\text{ Base cost dollar bin}}$	.593	-.160	.789	.070	.685	.667
	p value	**.015**	.553	**<.001**	.798	**.003**	**.005**
Individual Ordering Summary	M $ final receipt	11.98	14.05	9.21	10.92	11.67	12.24
	$N_{\text{Additional Item}} = N_{\text{AI}}$	3,726	905	657	481	5,769	14,571
	N_{Total}	13,659	3,528	4,297	2,146	23,630	52,583
	$N_{\text{AI}}/N_{\text{Total}} = k$	.273	.257	.153	.224	.244	.277
	$N_{\text{AI 1,2Above}}$	1,349	335	258	203	2,145	5,373
	$N_{\text{Total 1,2Above}}$	4,462	1,160	2,038	876	8,536	18,453
	$N_{\text{AI 1,2Below}}$	1,543	380	224	164	2,311	6,048
	$N_{\text{Total 1,2Below}}$	5,924	1,619	1,451	794	9,788	22,889
	$k_{\text{1,2Above}}$	.302	.289	.127	.232	.251	.291
	$k_{\text{1,2Below}}$	.260	.235	.154	.207	.236	.264
	z of $k_{\text{Above}} - k_{\text{Below}}$	**4.71**	**3.22**	**-2.34**	1.24	**2.39**	**6.09**
	p value	**<.001**	**.001**	**.019**	.214	**.017**	**<.001**
Credit					Cluster 2, *Credit & Dinner*		
16 ◊*k* values from Figure 3	M	.346	.292	.288	.311	.308	
	$\Delta k/\Delta$Base cost $ bin	0.0002	0.005	**0.023**	0.002	**0.006**	
	Durbin-Watson	2.30	**0.52**	1.03	1.34	1.72	
	$r_{k,\text{ Base cost dollar bin}}$	.018	.230	.825	.106	.522	
	p value	.948	.391	**<.001**	.697	**.038**	
Individual Ordering Summary	M $ final receipt	12.46	14.98	10.42	14.43	12.70	
	N_{AI}	5,039	1,741	1,212	810	8,802	
	N_{Total}	15,034	5,608	5,775	2,536	28,953	
	k	.335	.310	.210	.319	.315	
	$N_{\text{AI 1,2Above}}$	1,846	692	420	270	3,228	
	$N_{\text{Total 1,2Above}}$	4,948	1,962	2,151	856	9,917	
	$N_{\text{AI 1,2Below}}$	2,125	751	541	320	3,737	
	$N_{\text{Total 1,2Below}}$	6,925	2,564	2,525	1,087	13,101	
	$k_{\text{1,2Above}}$	.373	.353	.195	.315	.326	
	$k_{\text{1,2Below}}$	.307	.293	.214	.294	.285	
	z of $k_{\text{Above}} - k_{\text{Below}}$	**7.54**	**4.28**	-1.60	1.00	**6.58**	
	p value	**<.001**	**<.001**	.109	.317	**<.001**	

Note. Slope $m = \Delta k/\Delta$Base cost dollar bin and Durbin Watson statistic are from the univariate regression: $k = b + m \cdot$Base cost dollar bin; with 16 ◊k values from Figure 3. Critical values for Durbin Watson are d_l = 0.98 and d_u = 1.24. Just above values have remainder 1, or 2 when divided by 5 (Base cost bins 6, 7, 11, 12, 16, or 17) and are denoted 1,2Above and just below values, denoted 1,2Below, have remainder 3 or 4 when divided by 5 (bins 8, 9, 13, 14, 18, 19). All significance level p values based on 2-tailed test with boldfaced values when p< .05.

Rather than looking for patterns across all just above and just below *k* proportions, Table 3 focuses on *k* ordering behavior just above and just below the individual barrier values \$10 and \$15 by Cluster × Payment Type. This table examines whether there are significant differences between just above and just below *k* proportions at \$10 (base cost bins 11 or 12 versus 8 or 9) and at \$15 (base cost bins 16 or 17 versus 13 or 14). By focusing on each individual barrier, we can examine whether there exists a different intensity of differential order adding behavior at different barriers.

By drawing attention to behavior between barrier points, Table 4 examines the converse situation to that examined in Table 3. In particular, Table 4 compares *k*(*y*) behavior at the two adjacent bins farthest away from multiples of 5. Adding a \$3 or smaller item will not push the customer past the next higher barrier bin for the smaller of these two values but may well push the customer past the next higher barrier bin for the larger of these two values. Note that, in contrast with standard usage, the number that is 2 above the lower bound (for example, 7) *is smaller than* the number that is 2 below the upper bound (8). As with Table 3, by focusing on bins between each individual pair of barrier outcomes (7 versus 8, 12 versus 13, and 17 versus 18), we can examine whether there exists a different intensity of differential order adding behavior in different dollar ranges. Table 4 is organized by Meal Time (*Lunch* or *Dinner*) × Cluster × Payment Type. As with Table 2, three aggregated portions are included to the right in both Tables 3 and 4.

Table 3. Proportion of Individuals Ordering Additional Item, k, for Just Above $10 or $15 with Just Below $10 or $ 15 by Cluster × Payment Type

		Cluster 1, *Typical*		Cluster 3, *Discount & Expensive*		Cluster 4, *Weekday & Lunch*		Cluster 5, *Takeout & Cash*		Aggregated Across Clusters		Aggregated Across Cash & Credit	
	Focal price point	$10	$15	$10	$15	$10	$15	$10	$15	$10	$15	$10	$15
Cash	$N_{\text{AI 1,2Above}}$	564	418	154	140	70	51	44	50	832	659	2,178	1,843
	$N_{\text{Total 1,2Above}}$	1,686	1,313	443	551	308	141	285	169	2,722	2,174	6,340	5,576
	$N_{\text{AI 1,2Below}}$	655	539	76	185	110	43	71	58	912	825	2,363	2,076
	$N_{\text{Total 1,2Below}}$	3,028	1,808	354	716	1,014	255	361	301	4,757	3,080	10,628	7,041
	$k_{\text{1,2Above}}$	.335	.318	.348	.254	.227	.362	.154	.296	.306	.303	.344	.331
	$k_{\text{1,2Below}}$	.216	.298	.215	.258	.108	.169	.197	.193	.192	.268	.222	.295
	$k_{\text{Above}} - k_{\text{Below}}$	**.118**	.020	**.133**	-.004	**.119**	**.193**	-.042	**.103**	**.114**	**.035**	**.121**	**.036**
	z of $k_{\text{Above}} - k_{\text{Below}}$	**8.88**	1.21	**4.12**	-0.17	**5.32**	**4.32**	-1.40	**2.55**	**11.21**	**2.80**	**17.25**	**4.30**
	p value	**<.001**	.226	**<.001**	.862	**<.001**	**<.001**	.163	**.011**	**<.001**	**.005**	**<.001**	**<.001**
								Cluster 2, *Credit & Dinner*					
Credit	$N_{\text{AI 1,2Above}}$	775	570	333	327	129	150	109	137	1,346	1,184		
	$N_{\text{Total 1,2Above}}$	2,016	1,647	768	1,047	493	328	341	380	3,618	3,402		
	$N_{\text{AI 1,2Below}}$	1,009	658	109	344	256	107	77	142	1,451	1,251		
	$N_{\text{Total 1,2Below}}$	3,515	2,108	387	1,121	1,782	326	187	406	5,871	3,961		
	$k_{\text{1,2Above}}$	.384	.346	.434	.312	.262	.457	.320	.361	.372	.348		
	$k_{\text{1,2Below}}$	.287	.312	.282	.307	.144	.328	.412	.350	.247	.316		
	$k_{\text{Above}} - k_{\text{Below}}$	**.097**	**.034**	**.152**	.005	**.118**	**.129**	**-.092**	.011	**.125**	**.032**		
	z of $k_{\text{Above}} - k_{\text{Below}}$	**7.46**	**2.20**	**5.01**	0.27	**6.18**	**3.38**	**-2.12**	0.32	**12.96**	**2.93**		
	p value	**<.001**	**.028**	**<.001**	.784	**<.001**	**<.001**	**.034**	.752	**<.001**	**.003**		

Note. AI = Adding items. $k = N_{\text{AI}}/N_{\text{Total}}$. Just above values have remainder 1, or 2 when divided by 5 (Base cost bins 11 or 12 for $10 and 16 or 17 for $15) and are denoted 1,2Above. Just below values have remainder 3 or 4 when divided by 5 (bins 8 or 9 for $10 and 13 or 14 for $15) and are denoted 1,2Below. All significance level p values based on 2-tailed test with boldfaced values when $p < .05$.

Table 4. Order Adding Behavior Between Focal Point. Proportion of Individuals Ordering Additional Item, k, for 2 Above a Multiple of \$55 versus 2 Below the next Multiple of \$5 by Payment × Meal Time × Cluster

			Cluster 1, *Typical*			Cluster 3, *Discount & Expensive*			Cluster 4, *Weekday & Lunch*			Cluster 5, *Takeout & Cash*			Aggregated Across Clusters			Aggregated Cash & Credit		
Between values		2AboveL	7	12	17	7	12	17	7	12	17	7	12	17	7	12	17	7	12	17
		2BelowU	8	13	18	8	13	18	8	13	18	8	13	18	8	13	18	8	13	18
Cash	Lunch	$N_{\text{AI 2AboveL}}$	77	96	51	8	21	22	48	29	12	32	3	7	165	149	92	354	365	233
		$N_{\text{Total 2AboveL}}$	334	272	160	47	64	70	554	118	41	97	62	32	1,032	516	303	1,925	1,112	749
		$N_{\text{AI 2BelowU}}$	83	79	43	9	43	24	49	18	24	27	11	5	168	151	96	452	371	254
		$N_{\text{Total 2BelowU}}$	383	239	136	91	127	79	572	109	49	106	55	22	1,152	530	286	2,457	1,198	768
		k_{2AboveL}	.231	.353	.319	.170	.328	.314	.087	.246	.293	.330	.048	.219	.160	.289	.304	.184	.328	.311
		k_{2BelowU}	.217	.331	.316	.099	.339	.304	.086	.165	.490	.255	.200	.227	.146	.285	.336	.184	.310	.331
		$k_{\text{Above}} - k_{\text{Below}}$	.014	.022	.003	.071	-.010	.010	.001	.081	-.197	.075	**-.152**	-.009	.014	.004	-.032	.000	.019	-.020
		z of k_{Above}-k_{Below}	0.44	0.53	0.05	1.21	-0.14	0.14	0.06	1.50	-1.90	1.18	**-2.52**	-0.07	0.91	0.14	-0.83	-0.01	0.96	-0.82
		p value	.657	.594	.962	.227	.885	.890	.953	.134	.057	.239	**.012**	.941	.362	.890	.405	.995	.339	.413
	Dinner	$N_{\text{AI 2AboveL}}$	175	192	141	13	61	49	9	6	8	15	12	14	212	271	212	483	681	624
		$N_{\text{Total 2AboveL}}$	476	558	475	49	182	203	95	40	22	54	88	53	674	868	753	1,341	1,983	1,938
		$N_{\text{AI 2BelowU}}$	217	202	149	20	73	47	7	3	12	21	11	14	265	289	222	621	734	617
		$N_{\text{Total 2BelowU}}$	859	725	447	118	245	255	126	26	34	82	148	47	1,185	1,144	783	2,334	2,605	2,053
		k_{2AboveL}	.368	.344	.297	.265	.335	.241	.095	.150	.364	.278	.136	.264	.315	.312	.282	.360	.343	.322
		k_{2BelowU}	.253	.279	.333	.169	.298	.184	.056	.115	.353	.256	.074	.298	.224	.253	.284	.266	.282	.301
		$k_{\text{Above}} - k_{\text{Below}}$	**.115**	**.065**	-.036	.096	.037	.057	.039	.035	.011	.022	.062	-.034	**.091**	**.060**	-.002	**.094**	**.062**	.021
		z of k_{Above}-k_{Below}	**4.42**	**2.52**	-1.19	1.42	0.82	1.49	1.11	0.40	0.08	0.28	1.55	-0.37	**4.31**	**2.95**	-0.09	**5.99**	**4.48**	1.46
		p value	**<.001**	**.012**	.233	.157	.413	.136	.266	.689	.935	.779	.120	.708	**<.001**	**.003**	.931	**<.001**	**<.001**	.144
												Cluster 2, *Credit & Dinner*								
Credit	Lunch	$N_{\text{AI 2AboveL}}$	108	110	59	8	41	40	70	44	27	3	21	15	189	216	141			
		$N_{\text{Total 2AboveL}}$	263	274	173	34	119	128	559	167	109	37	36	36	893	596	446			
		$N_{\text{AI 2BelowU}}$	140	110	57	18	53	38	119	36	52	7	21	11	284	220	158			
		$N_{\text{Total 2BelowU}}$	379	308	174	98	183	129	792	137	126	36	40	53	1,305	668	482			
		k_{2AboveL}	.411	.401	.341	.235	.345	.313	.125	.263	.248	.081	.583	.417	.212	.362	.316			
		k_{2BelowU}	.369	.357	.328	.184	.290	.295	.150	.263	.413	.194	.525	.208	.218	.329	.328			
		$k_{\text{Above}} - k_{\text{Below}}$	.041	.044	.013	.052	.055	.018	-.025	.001	**-.165**	-.113	.058	**.209**	-.006	.033	-.012			
		z of k_{Above}-k_{Below}	1.06	1.10	0.27	0.65	1.01	0.31	-1.31	0.01	**-2.67**	-1.41	0.51	**2.13**	-0.33	1.23	-0.38			
		p value	.291	.271	.791	.514	.314	.755	.191	.989	**.008**	.159	.610	**.033**	.738	.217	.704			
	Dinner	$N_{\text{AI 2AboveL}}$	243	219	178	10	139	139	12	12	49	6	40	46	271	410	412			
		$N_{\text{Total 2AboveL}}$	501	653	562	42	306	422	83	32	74	41	124	127	667	1,115	1,185			
		$N_{\text{AI 2BelowU}}$	306	245	188	27	123	138	9	18	32	14	59	37	356	445	395			
		$N_{\text{Total 2BelowU}}$	896	835	517	101	402	484	113	44	70	39	180	199	1,149	1,461	1,270			
		k_{2AboveL}	.485	.335	.317	.238	.454	.329	.145	.375	.662	.146	.323	.362	.406	.368	.348			
		k_{2BelowU}	.342	.293	.364	.267	.306	.285	.080	.409	.457	.359	.328	.186	.310	.305	.311			
		$k_{\text{Above}} - k_{\text{Below}}$	**.144**	.042	-.047	-.029	**.148**	.044	.065	-.034	**.205**	**-.213**	-.005	**.176**	**.096**	**.063**	.037			
		z of k_{Above}-k_{Below}	**5.27**	1.73	-1.63	-0.36	**4.05**	1.44	1.45	-0.30	**2.48**	**-2.20**	-0.10	**3.56**	**4.17**	**3.37**	1.93			
		p value	**<.001**	.083	.104	.716	**<.001**	.149	.146	.764	**.013**	**.028**	.924	**<.001**	**<.001**	**<.001**	.053			

Note. AI = Adding items. $k = N_{\text{AI}}/N_{\text{Total}}$. Two above lower bound values have remainder 2 when divided by 5 (base cost bins 7, 12, and 17) are denoted 2AboveL. Two below upper bound values have remainder 3 when divided by 5 (bins 8, 13, and 18) are denoted 2BelowU. All significance level p values based on 2-tailed test with boldfaced values when p < .05.

RESULTS

Before examining barrier patterns within clusters it is worth noting a few general patterns that emerge from the data. For all clusters, the red dashed lines in Figure 3 are generally higher than blue for low final dollar bins and the reverse is true for high final dollar bins. This implies that lunch receipts are, on average, less than dinner receipts. This is confirmed by comparing average meal receipts in Table 1. A similar but more modest pattern emerges between weekday and weekend receipts. In general, weekend receipts are larger than weekday receipts but this difference is smaller than that between dinners than lunches. In comparing general within cluster patterns of *Cash* versus *Credit* we find the *Cash* average is lower than the *Credit* average. Within cluster *Credit* sales have a higher average proportion of individuals ordering an additional item than *Cash* sales. Each of these patterns conforms to ex-ante expectations.

Cluster 1, *Typical*, represents 42% of the restaurants (108/257) and comprises 55% of the receipts analyzed in Figure 3 (.55 = 28,893/52,583). Both the *Cash* and *Credit* panels exhibit clear evidence of barrier purchasing behavior, with a sinusoidal-like trend in $k(y)$ typically possessing troughs near a 1,2Below value and peaks near a 1,2Above value around expenditure barrier points. Both distributions of final receipt amounts (dashed lines) peak in bin 9 and have secondary peaks in bin 13. The *Cash* panel displays a slight positive linear trend in $k(y)$ while the Credit panel does not show such a trend (*Cash*Δ: $k\Delta/y = 0.008$, $p = .015$; *Credit*Δ: $k\Delta/y = 0.0002$, $p = .948$) and both patterns suggest dampening in their oscillatory behavior with larger expenditure points. When comparing the 1,2Below with the 1,2Above across all expenditure points we observe in Table 2 significant barrier behavior (*Cash*: .260 vs. .302, $p < .001$; *Credit*: .307 vs. .373, $p < .001$). This behavior is more striking around $10 (*Cash*: .216 vs. .335, $p < .001$; *Credit*: .287 vs. .384, $p < .001$) than around $15 (*Cash*: .298 vs. .318, $p = .226$, *Credit*: .312 vs. .346, $p = .028$) as seen in Table 3. This pattern is also more striking between barrier outcomes for smaller dollar comparisons than larger dollar comparisons for *Dinner* but not *Lunch* in Table 4. Both of the 7 – 8 *Dinner* differences are significant at $p < .001$ but neither of the 17 – 18 *Dinner* differences are significant ($p = .233$ for *Cash* and $p = .104$ for *Credit*).

A different pattern emerges in Cluster 4, *Weekday and Lunch*, where a large portion of the data falls below $10. More than one sixth of the *Cash* sales in Cluster 4 are in the $6 bin (16.9%) and more than 40% of receipts are in bins 6, 7, or 8. Note that this peak is one third higher than the next highest *Cash* peak, the $9 bin for Cluster 1 (1.33 = .169/.127). The *Credit* peak for Cluster 4 is at $9 and each bin from $6 through $10 exceeds 10% so that 63.4% of Cluster 4 *Credit* sales are in this five dollar window. Both forms of payment have lower additional item ordering at $6, $7 and $8 bins than later bins. When comparing the 1,2Below with the 1,2Above across all expenditure points, the results appear to be inverted with the general trend (*Cash*: .154 vs. .127, p = .019; *Credit*: .214 vs. .195, p = .109). This result appears to be a version of Simpson's paradox where the trends are not seen in the aggregate estimate. When the barrier points are examined separately, we see strong barrier behavior at $10 (*Cash*: .108 vs. .227, p < .001; *Credit*: .144 vs. 0.262, p < .001) and at $15 (*Cash*: .169 vs. .362, p < .001; *Credit*: .328 vs. .457, p < .001). It is clear the function $k(y)$, the probability of a consumer adding an item as a function of base cost, is not constant over the range examined (*Cash*Δ: $k\Delta/y$ = 0.018, p < .001; *Credit*Δ: $k\Delta/y$ = 0.023, p < .001). Interestingly, the only significant between barrier outcomes bin comparisons, the 17 – 18 differences, show significant opposing behavior in the *Credit* panel of Cluster 4 (*Lunch*: $k(17)$ = .248, $k(18)$ = .413, p = .008; *Dinner*: $k(17)$ = .662, $k(18)$ = .457, p = .013). Overall, the patterns in Cluster 4 are consistent with a consumer strategy of *minimizing* spending on lunches, as evidenced by the low add-on proportion at $6 and $7, and strong barrier behavior at both $10 and $15 with a smaller group of consumers willing to spend more and add on more often.

Cluster 3 has final receipt peaks in the $13-$14 range and again at $18, in line with its position as the expensive cluster. Both of these are just below values according to our definition. Contrary to our expectations, item adding behavior is high at $9 in the *Cash* panel but, in line with expectations, peaks occur at $11 and $12 before declining prior to $15. When comparing the 1,2Below with the 1,2Above across all expenditure points, the results are significant (*Cash*: .235 vs. .289, p < .001; *Credit*: .293 vs. .353, p < .001). However, while barrier behavior is clear at the $10 expenditure point (*Cash*: .215 vs. .348, p < .001; *Credit*: .282 vs. .434, p < .001) the behavior is not observed at the $15 expenditure point (*Cash*: .258 vs. .254, p =.862; *Credit*: .307 vs. .312, p = .784). Between barrier outcomes bin comparisons exhibit little significant differential k behavior with only one of the 12 comparisons significant for Cluster 3 (the 12 – 13 *Credit Dinner* comparison has $k(12)$ = .454, $k(13)$ = .306, p < .001).

Similar to Cluster 4, the *Takeout and Cash* Cluster 5 peak is also in the $6 bin (11.3%) as a result of the strong lunch showings there (of 16.4% and 15.7%). Interestingly, this panel displays markedly different lunch behavior than that observed in Cluster 4, where lunches purchased at a similar price did not typically include add-on items. This is may be due to the menu structure present in this cluster. When comparing the 1,2Below with the 1,2Above across all expenditure points, the results are not significant (*Cash*: .207 vs. .232, p =.214), and of note here is that this is one of the two Cluster × Payment Type combinations where the $10 expenditure point behavior is reversed with respect to barrier expectations (*Cash*: .197 vs. .154, p =.163). The data are, however, consistent with expectations and significant at the $15 expenditure point (*Cash*: .193 vs. .296, p = .011). The only significant between barrier outcomes bin comparison is also reversed with expectations (the 12 – 13 *Lunch Cash* comparison has $k(12) = .048$, $k(13) = .200$, $p = .012$).

Finally, the *Credit and Dinner* Cluster 2 exhibits peak bin receipts at $18, and the vast majority of receipt totals are for $10 or more. Similar to Cluster 5, the barrier behavior at $10 is reversed according to expectations, and while consistent in direction with expectations, neither the aggregated data nor the data at $15 are significant. Of note here is the potential barrier behavior near $20, where there is a clear local minimum for *k* in the $18 - 19 range concurrent with the maximum in final receipt percentage totals. This is confirmed by significant differential *k* behavior between 17 and 18 for both *Lunch* and *Dinner* (*Lunch*: $k(17) = .417$, $k(18) =.208$, $p = .033$; *Dinner*: $k(17) = .362$, $k(18) =.186$, $p < .001$).

It is worth noting that the patterns discerned from both Clusters 2 and 5 are based on smaller numbers of receipts than other clusters. Five *k* values are suppressed from each of these panels in Figure 3 due to having 10 or fewer base cost receipts in the bin for that category of purchases. For Cluster 5, this thinness occurs for high base cost bins and for Cluster 2, the reverse is true. Given these limitations, it is not surprising that the results for these clusters exhibit somewhat greater variability than those created from larger numbers of observations.

The two final panels in Figure 3 provide the same information aggregated across clusters. These panels show different patterns of $k(y)$ behavior for lunch (red and maroon) than dinner (blue and purple). Both lunch categories have minimum *k* at the $6 bin with low *k* values continuing through the $9 bin before increasing. By contrast, dinner purchases exhibit higher just above a multiple of 5 than just below a multiple of 5 $k(y)$ behavior except at the $6 bin.

The final aggregation in Table 2, based on 52,583 individual orders, shows that order adding behavior is 2.7% higher just above than just below multiples of five (.027 = .291 - .264). This difference has a *z* score of 6.09 and is significant at the $p < .001$ level. Equally strong results occur upon aggregation for individual barrier points in Table 3 where we see order adding is 12.1% higher just above $10 than just below $10 based on 16,968 orders (16,968 = 6,340 + 10,628) and 3.6% higher just above $15 than just below $10 based on 12,617 orders (12,617 = 5,576 + 7,041). These differences have *z* scores of 17.25 and 4.30, respectively, both of which are significant at the $p < .001$ level. The final aggregation in Table 4 shows no significant differential *k* behavior between barrier points for *Lunch* (with *p* values of .995, .339, and .413) but 9.4% higher at 7 than 8 for *Dinner* ($k(7) = .360$, $k(8) = .266$, $p < .001$) and 6.2% higher at 12 than 13 ($k(12) = .343$, $k(13) = .282$, $p < .001$).

DISCUSSION

An accurate understanding of consumer psychology is important for optimizing pricing and item suggestion strategies. This understanding includes the elucidation of potential barrier values for total expenditures that consumers use when making decisions. While some of the these values may be revealed using consumer surveys and focus groups, they may also be operating at a subconscious level in many instances, only being revealed after an analysis of the type presented here. In addition, the presence and strength of these values may vary for different clientele and in different dining scenarios and settings.

In this study we suggest a rationale for, and test the proposition that, individuals set reservation prices for online meal purchases using barrier points in multiples of $5. These values appear significant in consumer ordering behavior in a variety of restaurant types and meal settings. The richness of the dataset, spanning 257 restaurants, helps shield the analysis from specific menu/customer interactions that would clearly dominate a study of this type involving only a few participating restaurants. To simplify the interpretation of the analysis, we clustered restaurants into homogeneous groups. This allows us to more readily identify consumer trends within the various consumer groups. In addition to being statistically significant in most instances at the $10 and $15 expenditure points, the data often display practical significance at many of these price/meal combinations because of the large differentials observed there. For example, in the *Weekday and Lunch* group of restaurants, 24.8% of customers at a base cost of $11 or $12 added an item while only 13.1% of those at a base cost at $8 or $9 did so ($p < .001$). Order adding behavior in the *Typical* cluster at a base cost of $7 versus $8 shows a large differential for dinner (.428 vs. .298, $p < .001$) but not for lunch (.310 vs. .293, $p = .492$).

Recognition of consumer expenditure barriers is clearly an important facet of pricing strategy. This study suggests significant opportunity for targeting individuals making meal purchases with dynamic pricing strategies that move their total cost relative to demonstrated expenditure barrier points. Similar strategies have been discussed in the literature (Jiang, Shang, Kemerer, & Liu, 2011). With an ever increasing share of commerce taking place using digital interfaces, managers can utilize this opportunity to design pricing strategies most likely to increase total receipts. Bundling on the basis of price may prove more effective in many instances than more traditional commodity bundling (Adams & Yellen, 1976). An immediate example is the creation of a “personalized flash-sale,” where the price of an add-on item is dynamically altered based on the current status of an order and then offered to the consumer to move them close to an identified expenditure barrier. For consumers with orders at or near a barrier, it may prove more fruitful to offer a larger item or a collection of smaller add-ons simultaneously to push the individual to the next salient point where they may see greater incremental value capable of pulling them forward from the current expenditure barrier.

Because of the more complex dynamics at play when orders are placed by groups, we did not examine potential expenditure barriers in group ordering here. Moreover, while we have demonstrated the existence of expenditure barriers in $5 increments for online meal purchases, it is not clear from the dataset if this behavior translates into other consumer contexts or even if it is maintained in a more traditional dining setting where the individual does not order through a digital portal. Such questions will become increasingly important as more traditional restaurants move toward digital interfaces for customer ordering as dictated by efficiency and cost considerations.

It would be interesting to expand the model of expenditure barriers to venues outside the restaurant context. Multiple item purchasing is also common at grocery, department, and convenience stores. It would be instructive to apply the logic developed here to see if item adding behavior in the checkout line is functionally related to the base cost of items chosen prior to entering that line. The model of checkout behavior developed by Miranda (2008) could readily be expanded to analyze this question.

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