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Research Note

The Traveling Salesman Goes Shopping: The Systematic Deviations of Grocery Paths from TSP Optimality

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We examine grocery shopping paths using the traveling salesman problem (TSP) as a normative frame of reference. We define the TSP-path for each shopper as the shortest path that connects all of his purchases. We then decompose the length of each observed path into three components: the length of the TSP-path, the additional distance because of *order deviation* (i.e., not following the TSP-order of category purchases), and the additional distance because of *travel deviation* (i.e., not following the shortest point-to-point route). We explore the relationship between these deviations and different aspects of in-store shopping/purchase behavior. Among other things, our results suggest that (1) a large proportion of trip length is because of travel deviation; (2) paths that deviate substantially from the TSP solution are associated with larger shopping baskets; (3) order deviation is strongly associated with purchase behavior, while travel deviation is not; and (4) shoppers with paths closer to the TSP solution tend to buy more from frequently purchased product categories.

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1. Introduction

With the advent of new technologies, e.g., radio frequency identification (RFID), researchers are equipped with better data to explore in-store shopping behavior, adding value to the ubiquitous scanner data analyses that have been pervasive over the past 25 years (Guadagni and Little 1983). For example, Burke (1996) studied consumers' grocery shopping patterns using a virtual (simulated) store; Sorensen (2003) tabulated purchase and time-of-stay statistics at different locations within an actual grocery store; and Larson et al. (2005) categorized grocery paths using a clustering algorithm, and identified 14 different "canonical paths."

In contrast to these purely descriptive studies, we instead compare a large number of shopping paths and purchase baskets to the normative benchmark provided by the traveling salesman problem (TSP). In the classic TSP, the salesman has to visit a number of cities before returning to his original starting point. The objective is to choose his order of visitation to minimize his travel distance while visiting all the required cities. By analogy, in the grocery setting, we define the TSP-path as the shortest route that connects the entrance, all the products that a shopper purchased, and the checkout counter.

We compare each shopper's observed behavior with his TSP-path and document the systematic departures that emerge. We focus on two types of deviations: First, the shopper may not follow the exact shopping order suggested by the TSP-path. We define this type of departure as *order deviation*. Second, given the actual order of purchases the shopper has chosen (TSP-optimal or otherwise), he may not follow the shortest point-to-point route. We define this source of departure as *travel deviation*. Thus, every observed path is decomposed into three parts: the travel distance of the TSP solution, the additional distance because of order deviation, and the additional distance because of travel deviation.

This decomposition leads to a number of empirical questions: How similar is each observed grocery path to its corresponding TSP solution? How will the contribution of each deviation vary across trips? Will one component dominate the others? Taking things a step further, we study the relationship between order/travel deviations and other more "classic" trip characteristics such as the number of items purchased on each trip, the number of aisles traversed, and total time in store. For instance, will longer trips be associated with higher or lower order deviations? On the one hand, longer trips may be more organized; yet on the other hand, there are more opportunities for choosing a different order of visitation from the TSP solution. Another interesting issue is whether/how category purchase incidence is in any way related to order/travel deviations. For example, what is the relationship between order/travel deviations and the number of items purchased? Do shoppers who travel routes closer to the TSP-path tend to shop disproportionately in certain categories? Our goal is to answer the above questions empirically to better understand shopping patterns as a whole as well as the nature of the deviations that we document here.

Our research is in the same spirit as other papers in marketing/economics that have compared observed behavior to a well-established normative paradigm. For example, Camerer et al. (2004) analyzed behavior in economic games, comparing it with the normative prescription of the Nash equilibrium. Likewise, Meyer and Assuncao (1990) analyzed consumers' stockpiling strategies and documented the contexts in which consumers tend to underbuy or overbuy compared to their optimal solutions, calculated from sequential decision theory. In both cases, researchers took a logical optimality paradigm and carefully described how actual behavior departs from it. Other papers with similar goals include Houser et al. (2004), MacGregor et al. (1999, 2000), Polivanova (1974), Seale and Rapoport (2000), and Vickers et al. (2001).

The remainder of this paper is organized as follows. Section 2 discusses our analytical framework and how each observed path is decomposed into its TSP-path, order deviation, and travel deviation. Section 3 describes the data, and §4 discusses our empirical results. Finally, §5 concludes with a summary of our findings.

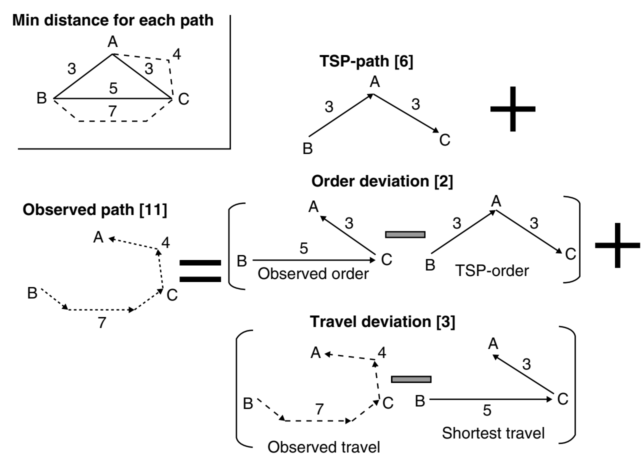
2. Analytic Framework

We define the TSP-path as the shortest path (in terms of total travel distance) that starts at the entrance, connects all of the observed purchases, and ends at checkout.[1] We obtain the TSP-path using two algorithms commonly used to solve the TSP: exhaustive search (Lawler 1985) and simulated annealing (Goffe 1994), which are outlined in the Technical Appendix A.[2]

[1] Alternatively, one could consider the path that minimizes shopping time instead of distance. However, as discussed in §3, our data are not from a longitudinal panel, so it is impossible to tease apart individual speed differences among shoppers. Thus we cannot make any normative assessments about shopping time, per se.

[2] The Technical Appendix is available online at http://mktsci.pubs.informs.org.

Figure 1 Deviation Decomposition



Once the TSP-path is derived, we carefully examine differences between it and its actual counterpart. Two types of deviations are considered: order deviation and travel deviation. We illustrate these concepts in Figure 1.

In this simple example, the TSP-optimal order is $B \to A \to C$, with a total travel distance of $3+3=6$ units. The observed shopping order, $B \to C \to A$, results in a longer travel distance ($5+3=8$), assuming that the shortest point-to-point paths are taken when traveling between two locations. We define the difference between the travel distance of the optimal order and the observed order as order deviation, which in this case is $8-6=2$ units.

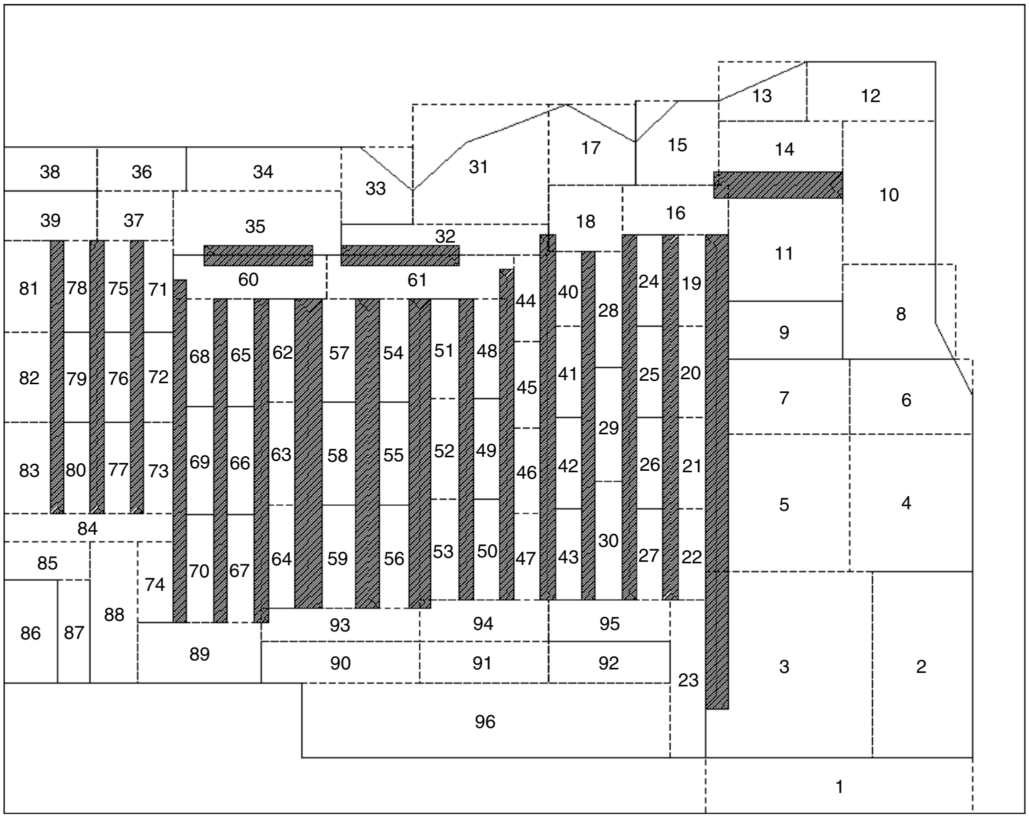
To measure travel deviation, we take the observed order ($B \to C \to A$) as given and look for excessively long routes when traveling from one location to the next. In Figure 1, although the shortest path from B to C requires five units of travel distance, the shopper took a more indirect path that required seven units. Likewise, the shopper incurred $4-3=1$ units of travel deviation when traveling from C to A. Thus, there is a total of three units of travel deviation.

Thus, each observed path can be decomposed into three components: the TSP-path, order deviation, and travel deviation. Adding these three components together equals the total distance traveled. In our example above, the decomposition can be described by the following equation:[3]

$$\text{Observed Path} = \text{TSP-Path} + \text{Order Deviation} + \text{Travel Deviation}$$
$$11 = 6 + 2 + 3. \tag{1}$$

[3] To the best of our knowledge, this is the first time this decomposition has been derived and represents a contribution of this research that may aid researchers more broadly.

Figure 2 Grocery Store Divided into 96 Zones



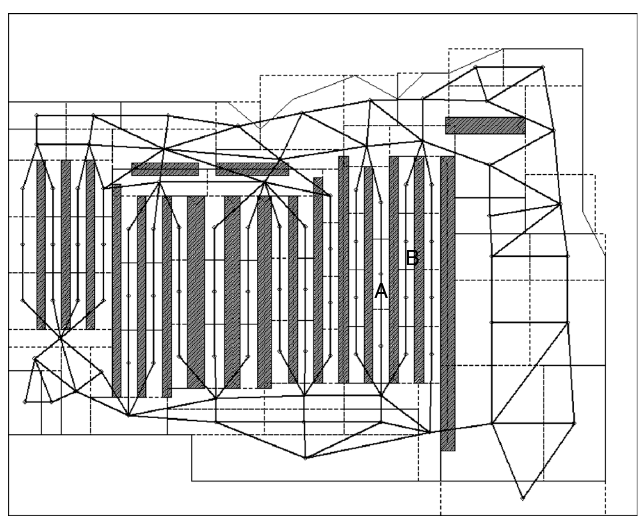
3. Data

We apply our analytic framework to a data set that contains consumers' shopping path data together with their purchases from a large supermarket in the eastern United States. We obtained our data from Sorensen Associates, an in-store research company that tracks shoppers' movement using its proprietary PathTracker® system based on RFID technology (Sorensen 2003). A small RFID tag is affixed under each shopping cart and emits a uniquely coded signal every five seconds. This signal is then picked up by an array of antennae located throughout the store that can pinpoint the precise location of the shopping cart[4] over time.

Our data preparation procedures, described more fully in Hui et al. (2007) and outlined in Technical Appendix B, which can be found at http://mktsci.pubs.informs.org, yielded a total of 993 shopping paths and their corresponding purchase records. The procedure described in Hui et al. (2007) allows us to discretize the grocery store into a graph with 96 nodes, thus making each cart movement a selection among a finite set of edges. The division of the grocery store into zones is shown graphically in Figures 2 and 3.

For each path, we extract a number of key summary statistics (shown in Table 1) on shoppers' movement and purchases. These statistics include the total number of product categories purchased (out of a total of 116), total path distance traveled in the store, the number of unique zones visited (out of

Figure 3 Grocery Store Represented By a Graph of 96 Nodes



[4] We recognize that the shopper's cart is a noisy proxy for his or her exact location, yet it is a significant advance over having no tracking data. As per Sorensen (2003), more precise technologies are likely to be available soon.

Table 1 Key Summary Statistics of the PathTracker Data Set

	Mean	Std. dev.	Min	Max
Number of product categories purchased	7.1	4.0	2.0	25.0
Total travel distance (in feet)	2,513.0	1,193.4	233.9	11,234.4
Total in-store time (minutes)	49.8	25.2	7.9	238.3
Number of unique zones visited	49.9	14.2	5.0	83.0
Number of unique aisles entered	7.3	3.4	0.0	15.0
Number of unique aisles transversed	2.6	1.7	0.0	9.0

the aforementioned 96 zones), total time (in minutes) spent in the store, and the number of unique aisles that each shopper entered and traversed. Table 2 lists the top 10 categories purchased based on the proportion of shoppers who made at least one purchase in each category. In §4, we relate these measures to our TSP-decomposition results.

Table 3 Summary of Our Empirical Findings

TSP decomposition (§4.1: Table 4 and Figure 4)
- (a) There is a great deal of variability in TSP-optimality across paths (5%–95%; average = 28%).
- (b) Order deviation is small (always < 20%; average = 3%).
- (c) Travel deviation is large (average = 69%).

Relationship between deviations, basket size, and path characteristics (§4.2: Table 5)
- (a) Shoppers with paths that deviate more from TSP tends to (i) visit more zones, (ii) enter/traverse more aisles, (iii) spend longer time in store, and (iv) purchase more.
- (b) Order deviation is strongly correlated to basket size.
- (c) Travel deviation is uncorrelated to basket size.

Relationship between deviations and basket composition (§4.3: Table 6)
- (a) Paths closest to TSP (Group 1) tend to buy more frequently purchased categories.
- (b) Paths with low order deviation (Groups 1 and 3) tend to buy more produce, deli, and prepackaged goods.
- (c) Paths with high order deviation (Groups 2 and 4) tend to buy more from categories that are less frequently purchased.

4. Results

This section presents our empirical findings, which are summarized in Table 3. Section 4.1 describes the decomposition of paths into its TSP-path, order deviation, and travel deviation. Section 4.2 studies the relationship between order/travel deviations, basket size, and shopping path. Section 4.3 looks at the relationship between order/travel deviations and product categories purchased.

4.1. TSP Decomposition

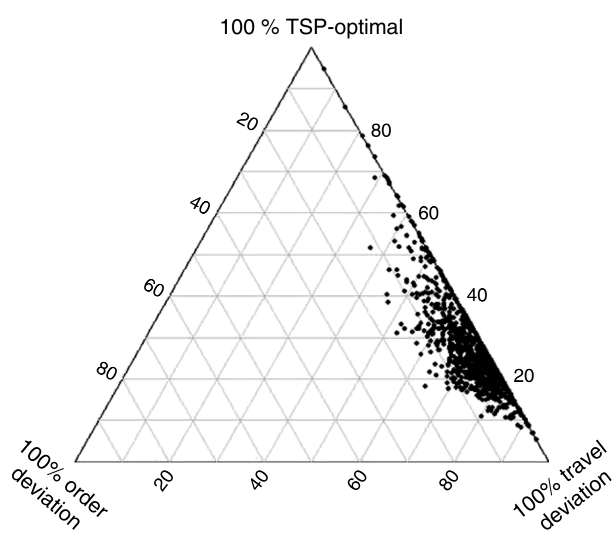
The fractions of observed travel distance associated with the TSP-path, order deviation, and travel deviation, for each of the 993 paths, are shown graphically in the triangle plot in Figure 4. The associated summary statistics are contained in Table 4. The triangle plot allows us to easily visualize the relationship among three variables that sum to 1. This figure yields several immediate insights. First, there is a great deal of variability in the decomposition of shoppers' paths, relative to the TSP-path, across the 993 trips. The percentage of total travel distance because of the TSP-path ranges from a low of approximately 5% to a high around 95%, with an average of about 28%. In contrast, the extent of order deviation is quite limited—never exceeding 20%. This suggests that shoppers, in general, choose an order for their purchases that is fairly close or the same as the order suggested by the TSP solution.

Most of the trips lie in the lower right corner of Figure 4, indicating that travel deviation accounts for a large portion of the travel distance for the majority of grocery trips. So while the order of purchases is close to that of the TSP-path, shoppers spend a large portion of their in-store trip not following the shortest point-to-point routes. One potential reason (among others) for these large deviations is that shop-

Table 2 Top 10 Categories Purchased

Category	Proportion of shoppers who purchase the product category (%)
Fruits	55.3
Vegetables	52.2
Butter/cheese/cream	40.0
Carbonated beverages	25.4
Salty snacks	24.4
Cookies and crackers	23.9
Milk	23.7
Ice cream	20.7
Loaf bread	20.5
Cereal (ready-to-eat)	18.1

Figure 4 Triangle Plot for Optimal Path, Order Deviation, and Travel Deviation



Note. The different fonts and orientation of the labels indicate which scale corresponds to each dimension.

Table 4 **Summary Statistics from a TSP-Decomposition Analysis**

	Mean	Std. dev.	Mean (%)	Min (%)	Max (%)
TSP-path	612.0	189.4	27.5	5.4	94.7
Order deviation	89.5	107.9	3.1	0.0	17.1
Travel deviation	1,811.5	1,021.6	69.4	5.3	94.6
Total distance	2,513.0	1,193.4			

pers may deliberately plan to visit some product categories to see whether promotions are available, but may not necessarily purchase from those categories. We investigate this issue through a sensitivity analysis in the appendix.

4.2. Relationship Between Deviations, Shopping Basket Size, and Trip Characteristics

To explore the relationship between order/travel deviations and the characteristics of shopping paths mentioned earlier, we divide the 993 trips into four groups based on a median split along each deviation dimension. The summary statistics for each group are shown in Table 5, along with relevant visit and purchase characteristics as described in aggregate in Table 1.

The first, and most obvious, contrast is between Group 1 (low on both deviations) versus Group 4 (high on both). It should come as no surprise that shoppers who exhibit the greatest deviations from the TSP solution tend to visit more zones, which means entering (and traversing) more aisles. It is not as obvious, a priori, that these shoppers will also buy more products, but the difference in basket size is large and highly significant ($p < 0.001$). Furthermore, we also note that the total time in the store is larger for shoppers in Group 4 compared with Group 1 ($p < 0.001$).

A more illuminating contrast is between the two intermediate groups. In comparing Group 2 to Group 3, we see that order deviation tends to be more influential than travel deviation in generating long trips with more aisles visits/traverses and larger baskets of purchased items. However, a closer look at these two groups reveals some interesting differences that reflect the impact of order versus travel deviation. For instance, while the average basket size is over 50% greater for Group 2 versus Group 3, the mean number of zones visited is barely 10% larger. The latter difference is still statistically significant ($p = 0.003$), but it is indicative of the notion that the shoppers who exhibit a lot of travel deviation are visiting an "excessive number" of zones relative to the number of items that they purchase.

When we aggregate the data in Table 5 to look at each of the deviation dimensions by itself, we see another trend involving basket size. Specifically, mean basket size is far smaller for the groups with low order deviation, i.e., Groups 1 and 3 (mean $= 5.1$) compared with those with high order deviation, i.e., Groups 2 and 4 (mean $= 9.1$, $p < 0.001$). This observation is consistent with MacGregor and Ormerod (1996), who found that people's performance in TSP problems generally worsens (i.e., more order deviation in our context) when they are given more locations to visit. But when we aggregate along travel deviation (Groups 1 and 2 versus Groups 3 and 4) we see no difference in basket size (means of 7.0 and 7.2, respectively, $p = 0.35$). Thus, while travel deviation accounts for a large portion of most trips, order deviation has a much stronger association with purchasing behavior.

Table 5 **Summary Statistics of Clusters of Shoppers (H, High; L, Low)**

	Group 1	Group 2	Group 3	Group 4
Order deviation (H/L)	L	H	L	H
Travel deviation (H/L)	L	L	H	H
Number of shoppers	203	294	294	202
Mean percent of order deviation (%)	0.4	6.3	0.6	4.8
Mean percent of travel deviation (%)	59.5	62.5	78.6	76.1
Mean unique number of zones visited	38.2	52.1	48.9	59.7
Mean basket size (number of categories)	4.5	8.7	5.6	9.6
Mean unique number of aisles entered	4.7	7.7	7.1	9.6
Mean unique number of aisles traversed	1.4	2.8	2.5	3.7
Mean in-store time (in minutes)	28.8	47.9	50.5	72.2

4.3. Relationship Between Order/Travel Deviations and Basket Composition

Next, we study which product categories are most strongly associated with each of the four groups. To perform this analysis in a fair manner, we must normalize for the differences in basket size. To do so, we compute the number of purchases of each category for each group and divide this by the total basket size of each group; these proportions are then compared across groups. Table 6 displays the product categories that are significantly (at $p < 0.05$) overrepresented in each group. We find that produce (e.g., fruits and vegetables), deli products (e.g., cheese/milk), and prepackaged products tend to be associated with the groups that have low levels of order deviation; they seem to correspond to a well-organized shopping trip with a specific purpose, e.g., a shopper who brings a shopping list to shop for frequently purchased items. Along these lines, note that four of the 10 most frequently purchased categories (in Table 2) are overrepresented in Group 1. On the other hand, less frequently purchased household products are associated with higher order deviations. These purchases may correspond to a more impulsive shopping trip;

Table 6 Comparison of Product Categories Purchased for Each Group, Controlling for Basket Size

Category	Group 1 (%)	Group 2 (%)	Group 3 (%)	Group 4 (%)	Overall (%)
Categories overrepresented in Group 1 ($p < 0.05$)					
Butter/cheese/cream	7.4	5.9	5.1	4.9	5.6
Milk	5.4	3.5	3.1	2.4	3.3
Meat/poultry/seafood manufactured prepack	2.6	1.3	1.2	1.7	1.5
Prepackaged, deli-prepared lunch	0.4	0.2	0.0	0.2	0.2
Fruits	10.9	6.4	9.7	6.5	7.8
Vegetables	9.8	5.8	10.1	6.0	7.4
Tobacco	1.3	0.4	0.8	0.5	0.7
Categories overrepresented in Group 2 ($p < 0.05$)					
Pudding/dry dessert	0.3	0.5	0.1	0.3	0.3
Tea	0.0	0.2	0.0	0.2	0.1
Canned meat	0.2	0.4	0.0	0.1	0.2
Pasta	0.5	1.3	0.8	1.0	1.0
Paper towels	0.5	0.9	0.7	0.4	0.7
Prepared food/dry dinner	0.3	1.4	0.9	1.3	1.1
Categories overrepresented in Group 3 ($p < 0.05$)					
Candy/gum/mint	2.6	2.6	3.3	1.9	2.6
Fruits	10.9	6.4	9.7	6.5	7.8
Vegetables	9.8	5.8	10.1	6.0	7.4
Categories overrepresented in Group 4 ($p < 0.05$)					
Baby food	0.2	0.0	0.2	0.5	0.2
Bagels/breadsticks	0.3	0.8	0.6	1.1	0.8
Bottled water	0.9	0.7	1.0	1.8	1.1
Coffee	0.2	0.7	0.3	1.0	0.6
Cookies and crackers	3.0	3.4	2.6	4.1	3.4
Frozen pizza/snacks	1.0	1.1	1.2	2.1	1.4
Household cleaners	0.4	0.6	0.4	1.0	0.7

on such trips, the shoppers may be shopping casually and choosing categories as they go along, without much concern about planning their trip. This results in a longer shopping path and a seemingly haphazard path between purchases. Alternatively, it is also possible that these are "price shoppers" who are looking for promotions, an issue that we address using a sensitivity analysis in the appendix. A further explanation is that the location of less frequently purchased items is more unknown, leading to greater travel deviation.

5. Conclusion

In this research, we analyzed grocery shopping paths using the TSP as a normative frame of reference. We decomposed the systematic deviations between the observed path and the corresponding solution of the TSP problem into two components: order deviation and travel deviation, and studied the relationship among these measures, purchase behavior, and shopping path characteristics.

Our results, as summarized in Table 3, offer a mixed answer to a question we raised in §1: How similar are grocery trips to TSP-paths? On the one hand, relatively few of them have a proportion of distance because of TSP-path that captures over 50% of their travel distance, but on the other hand, the degree of order deviation is very low in every case—never exceeding 20% of the total distance. Thus shoppers tend to pick up their purchased products in an order close to that suggested by the TSP but tend to depart from the shortest point-to-point path (i.e., travel deviations) as they move through the store.

Furthermore, our analyses reveal consistent patterns about the interrelationship between order deviation and other characteristics of the trip. Specifically, trips with high order deviation tend to be longer trips with a greater number of product categories purchased and in-store time. Travel deviation is also associated with longer trips but has no association with the overall basket size. We also find that trips with lower order deviation tend to be associated with frequently purchased categories. While these results have significant face validity, we believe that they were not obvious a priori. We hope that our results will act as a springboard for future research in this area.

Acknowledgments

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Appendix. Sensitivity Analysis

The decomposition analysis in §4.1 is based on the assumption that shoppers come to the store with a fixed shopping list. In reality, many category purchases are unplanned (Bucklin and Lattin 1991), and a shopper may plan to visit some categories to check for promotions but may not purchase from them if a suitable deal is not available. We conducted two sensitivity analyses to study how these violations of the "fixed shopping list" assumption affect our results.

In the first sensitivity analysis, we randomly assign, for each trip, some of the purchases to be "unplanned," then we recompute the TSP-decomposition based on the reduced set of categories. The table below shows the results when 10%, 20%, 30%, 40%, and 50% of observed purchases are treated as unplanned.

Unplanned (%)	TSP-path (%)	Order (%)	Travel (%)
0	27.5	3.1	69.4
10	27.3	3.0	69.7
20	26.4	2.6	71.0
30	25.5	2.3	72.2
40	24.0	1.8	74.2
50	22.1	1.3	76.6

By allowing some of the category purchases to be unplanned, the TSP-optimal portion of each path is reduced.

This is expected because while the total observed distance is unchanged, the optimal distance (i.e., the minimum distance that the consumer needs to travel to complete his planned purchases) is reduced, thus reducing the extent of TSP-optimality (from 27.5% under the original no-unplanned purchase scenario to 22.1% when 50% of purchases are treated as unplanned). Because the movements toward unplanned purchases are treated as deviations from the main path, the fraction assigned to travel deviation therefore increases (from 69.4% to 76.6% as we go from 0% to 50% unplanned purchases). On the other hand, the extent of order deviation decreases (from 3.1% to 1.3%) because of the removal of these unplanned purchases from the original shopping list.

In the second sensitivity analysis, we randomly add m categories to each consumer's shopping list to represent categories (store zones) that she chose to visit but did not purchase from. The results are shown in the table below.

m	TSP-path (%)	Order (%)	Travel (%)
0	27.5	3.1	69.4
1	29.8	3.8	66.4
2	31.7	4.3	64.0
3	33.2	5.2	61.6
4	34.8	5.8	59.5
5	36.1	5.9	58.0

By allowing some category visits to be planned but not purchased, the fraction of the trip accounted for by travel deviation decreases from 69.4% to 58.0% as m rises from 0 to 5. This is because a portion of the travel deviation is now treated as planned *visitation* of certain categories. In addition, because the total observed trip length remains the same while the optimal path becomes longer, the fraction of distance because of the TSP-path goes up (from 27.5% to 36.1%). Finally, the fraction of order deviation goes up because of the inclusion of these additional product categories in the consumers' shopping list.

The above sensitivity analyses are valuable in three respects: (1) They show that our results are reasonably invariant with respect to violations of the TSP assumptions, namely, unplanned purchases and category visits that are planned but do not result in purchases; (2) they allow us to explore the directionality and magnitude of how our decomposition results are affected when the fixed shopping list assumption is violated; and (3) they suggest that part of the travel deviation can be attributed to consumer search behavior.

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