Do stockouts undermine immediate and future sales?

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Abstract

Purpose – Our aim is to identify immediate and future customer behavior in response to stockouts in a business-to-business wholesale environment.

Design/methodology/approach – We perform a statistical analysis of historical customer order and delivery data of a tool wholesaler and distributor over a period of four years. We investigate if there is any significant correlation between customer service (defined in terms of timely delivery) and order fill rate, as well as between customer service and the rate of future demand, where by fill rate we mean the fraction of the order that is eventually materialized, i.e., is not cancelled.

Findings – We find that for customers who order frequently, stockouts do have an adverse effect on the fill rate of their orders and on the frequency (but not the value) of their future demand, but this latter effect seems to be more short- than long-term.

Originality/value – Most studies on the effects of stockouts measure immediate reported/intended consumer purchase incidence and choice decision behavior in response to stockouts in retail environments, based on surveys. This study looks at how stockouts affect future demand in a wholesale environment, based on historical behavioral data analysis.

Keywords – Stockouts; Lost sales; Future demand; Statistical analysis; Historical data

Paper type – Research paper

A stockout occurs whenever an item is demanded from a supplier but can not be delivered because it is temporarily not in stock. In the short run, stockouts may incur backorder and/or lost sales costs. Backorder costs typically include extra costs for administration, price discounts or contractual penalties for late deliveries, expediting material handling and transportation, the potential interest on the profit tied up in the backorder, etc. Lost sales costs include the potential profit loss of the sale if all or part of the sale is lost, contractual penalties for failure to deliver, etc. Besides backorder and lost sales costs, which can be directly measured, a stockout may also incur a less tangible cost in the long run. This cost is related to the loss of customer goodwill. Intuition suggests that a customer who experiences a stockout from a supplier may think twice before placing another order in the future to the same supplier or, even worse, may inform other customers about the disservice he received and influence them into defecting in the future too. In other words, the service level provided by a
supplier may influence his future demand and therefore sales. In the short run, sales may fall short of demand when customers experience stockouts and choose not to backorder. In the long run, demand itself may decline as customers who experience excessive stockouts shift temporarily or even permanently to more reliable sources. In general, stockout costs are different for wholesalers/distributors than they are for manufacturers, and depend on whether the final customer switches brands or switches sizes or varieties of a brand in response to a stockout.

The quantification of stockout costs has long been a difficult and unsatisfactorily resolved issue in the literature. As Gardner (1980) puts it, shortage cost parameters are no more real than the gods of Olympus. Nonetheless, the effects of stockouts on customer behavior have been studied quite extensively mostly by the logistics research community and to a lesser extent by the inventory research community. Much of the work reported in the logistics research literature is based on interviews, surveys, and laboratory experiments, mostly on the short-term effects of stockouts, while the work in the inventory management literature focuses on the development and analysis of mathematical inventory models that assume a certain functional dependence of the demand on customer service.

In this paper, we investigate the effect of stockouts on the present and future sales of a firm by performing a statistical analysis of historical customer order and delivery data of a tool wholesaler and distributor, over a period of four years. The method that we use is simple. For the nine most important customers (retailers) of the wholesaler, whose data we were given access to, we examine if there is any significant correlation between customer service and the order fill rate, as well as between customer service and the rate of future demand, where by fill rate we mean the fraction of the order that is eventually materialized, i.e., is not cancelled.

Our initial findings are that 1) for four customers, stockouts have a significant adverse effect on the order fill rate, 2) for eight customers, they have a significant adverse effect on the frequency of future sales, and 3) for five of these eight customers, they also have a significant adverse effect on the monetary value of future orders.

These initial findings are obtained after applying repeatedly many single-context hypothesis tests, one for each customer. A well-known problem in statistics is that if one performs many such tests, one is likely to find false positives (erroneous significant results). To tackle this problem, we use Holm’s stepdown method to arrive at more conservative conclusions regarding the existence of significant correlations. We also explore if the effects of stockouts on future sales are short-term or long-term.
After applying Holm’s method, our conservative conclusions are that for the three most frequent customers, stockouts have a significant adverse effect on the order fill rate. Moreover, for two of these customers, stockouts also have a significant adverse effect on the frequency but not on the monetary value of future orders. Also, the latter effect seems to be more short- than long-term. The customer whose future sales are not affected by stockouts, even though his fill rate is affected, is the only customer who owned by the wholesaler.

We are not aware of any studies on the effects of stockouts in a wholesale environment that rely solely on observed order and delivery data and not on data extracted from interviews/surveys, so in this respect our work adds a contribution to the related literature. We hope that the empirical results of our analysis may provide useful information to researchers who set out to develop and analyze realistic models of supplier-customer behavior in a business-to-business environment.

**Literature review**

Most of the research on the effects of stockouts reported in the logistics research literature has focused on identifying and explaining consumer reaction to stockouts in retail settings. Such reaction may include item (brand and/or variety) or purchase quantity switching, cancellation or deferral of purchase, store switching, etc. A number of studies postulate some decision model with alternative possible outcomes and courses of action of consumers and retailers following a stockout, and estimate the parameters (probabilities, costs, etc.) of that model via interviews and/or mail surveys.

Nielsen (1968a, b) documents the frequency of stockouts observed for items sold in supermarkets. In contrast to prior stockout studies that try to estimate the cost of a stockout on the basis of unsold inventory only, this study looks into consumer behavior. When recording stockouts, a distinction is made between availability of product on shelves and availability in the store, the latter meaning that the product is only available in the store backroom. The study also reports breakdowns for product categories, weekdays, levels of brand loyalty captured by certain product categories, and most importantly substitute-delay-or-leave (SDL) response. More specifically, the study finds that 48% of the customers who face a stockout substitute the missing item, 24% delay their purchase until the store receives the missing item, and 28% look for the item in another store.

Walter and Grabner (1975) design a model to describe the decision alternatives of a customer that encounters a stockout in a retail store, and conduct an empirical test of that model in liquor stores operated by the Ohio Department of Liquor Control. They report that
83% of the respondents would substitute the missing item, 3% would delay their purchase until the store receives a new shipment of the out-of-stock product, and 14% would switch to another store. When customers are asked what they would do on their next shopping trip if a desired item were out of stock on their two previous trips (repeated stockout situation), 40% indicate that they would shop at a different store, 32.5% would expect the item to be in stock in their third attempt, 24.5% would substitute the requested item with another item at the same price range, and only 3% would order the missing item. Note that there is no price competition in the model, since all liquor sales at the time of the study were only in state-controlled stores and all prices were uniform throughout the state.

Shycon and Sprague (1975) highlight the implications of stockouts in a producer's retail outlet and find that often the delayed items are dropped from the retail inventory, as a reprisal for supplier service failures, which in turn results in decreased future sales for the supplier. They provide the justification and procedure involved in determining the cost of poor customer service. They show from empirical data that stockout delay costs in the food industry are strongly convex increasing even without taking opportunity costs into account.

Schary and Becker (1978) report the effects of a regional beer strike in which stockouts occurred in selected brands. Using brand share as the dependent variable, stockout effects are judged to be more short- than long-run. Schary and Christopher (1979) develop a model which identifies stockout response in relation to store and product decisions by consumers. They compare this model to evidence of actual response to stockout situations collected at two units of a British supermarket chain. Their findings suggest that stockout perception is not universal and that reaction to stockouts influence the total image of the store. They report that 22% of the respondents would substitute the missing item, 30% would delay their purchase, and 48% would switch to another store.

Zinszer and Lesser (1981) look at how stockouts affect consumers of different demographic characteristics, whether the item is on sale and how the stockout affects store image and intended future patronage. Badinelli (1986) repeatedly asks decision makers to specify their marginal exchange rate between on-hand inventory and backorders, and then uses the relatively more exact holding cost to estimate the shortage cost function through regression.

Emmelhainz et al. (1991) report the responses to an in-store interview of consumers who experience a stockout on items removed from the grocery shelves by researchers. They find that 73% of consumers substitute the missing item, 13% delay their purchase with the intention of buying the out-of-stock item at a later time, and 14% switch to another store.
This is one of the first studies where the researchers manipulate the actual stockouts on the retail shelf.

Dion and Banting (1995) report the results of a study on the perceived consequences for business-to-business market buyers of being stocked out by their supplier and their repurchase loyalty on the next purchase occasion. This study draws data from personal interviews and mail surveys. Buyers report lost sales and costly production disruptions resulting from the stockouts. The results show that buyers often seek an alternate supplier in the face of a stockout, but the majority returns to the original supplier on the next purchase occasion.

Campo et al. (2000) develop a theoretical model, based on consumer decision processes and utility-maximization concepts, that links observable characteristics of products, consumers, and situations to reactions to stockouts, within a product category. The relationships in their model explain some of the differences in stockout effects observed in previous studies. They empirically test the significance and relative importance of the impact of the potential determinants of stockout responses that they hypothesize in their model on data that they collect by means of a questionnaire in a supermarket store.

Zinn and Liu (2001) report results of an interview-based study of consumer short-term response to stockouts. They first compare the perceptions of consumers who recently experienced a stockout with those who did not. They then extend the literature by measuring a number of consumer specific (e.g., price shopper), situational (e.g. surprise with stockout), store-specific (e.g., perceived distance to a competing store) and demographic variables and then relating them to each of the consumer responses outlined above. Their results show that consumers appear able to isolate a recent stockout experience from their perception of other dimensions of the store's image. The results also suggest that demographic variables are not significant correlates of SDL behavior and that the majority of variables that are significant correlates of SDL behavior are situational. They report that 36% of the respondents would substitute the missing item, 25% would delay their purchase, and 39% would switch to another store. Finally, the strongest impact on the delay and leave behaviors is concentrated on two variables: store prices and surprise about the stockout.

Campo et al. (2004) investigate consumer reactions to stockouts – which are unexpected and temporary in nature – as opposed to permanent assortment reductions (PAR). Their results indicate that retailer losses incurred in case of a PAR may be substantially larger than those in case of a stockout for the same item. The results further suggest that stockout losses
may disproportionately grow with stockout frequency and duration, emphasizing the need to keep their occurrence and length within limits.

Finally, van Woensel et al. (2007) identify consumer behavior with regard to stockouts of perishable products, such as bakery bread. They observe that for perishable products, consumers have a relatively high willingness to substitute or purchase at another store.

There also exist a limited number of studies on the effects of stockouts that are based on laboratory experiments.

Charlton and Ehrenberg (1976) is one example in which a panel of consumers in the UK is repeatedly offered the opportunity to buy certain artificial brands of a detergent. The study examines the effects of price differentials, a promotion, advertising, a stockout condition, the introduction of a new product, and certain weak forms of price differentiation on consumer dynamics, i.e., on how people change their purchasing habits. As far as the effects of the stockout condition is concerned, it is found that market shares and category sales return to their pre-stockout levels with no apparent long-term effects.

Motes and Castleberry (1985) repeat the same type of experiment using a real potato chip brand and find that market shares do not return to their pre-stockout levels whereas category sales do. Their results indicate a brand switch reaction to the stockout followed by a return to the preferred brand once the stockout condition is eliminated. Similarly to Charlton and Ehrenberg (1976), this study does not consider the possibility of switching stores in response to the stockout.

Fitzsimons (2000) runs four laboratory experiments involving stockouts in a consumer choice context. The results of the experiments suggest that consumer response to stockouts is driven in large part by two factors: the effect of a stockout on the difficulty of making a choice from the set and the degree of personal commitment to the out-of-stock alternative.

All of the above works, those they rely on surveys measuring reported or intended behavior, and those that are based on laboratory experiments, focus mainly on the immediate impact of stockouts on purchase incidence and choice decisions but fail to look at the cumulative effects of stockouts over time. Nonetheless, there exist a limited number of studies that examine how stockouts affect future long-term demand of retailers, based on historical behavioral data analysis.

Straughn (1991) is one of the first to use scanner data in a stockout study. She attempts to estimate the effects of stockouts on brand share for candy bars. The short-term effect is negligible. The long-term effect, defined as more than five weeks following the stockout condition, is substantial. The decline in brand share averages 10%.
Campo et al. (2003) explore the impact of retail stockouts on whether, how much, and what to buy, by adjusting traditional purchase incidence, quantity and choice models, so as to account for stockout effects. Their study is based on scanner panel data of a large European supermarket chain. They estimate that stockouts may reduce the probability of purchase incidence, lead to the purchase of smaller quantities, and induce asymmetric choice shifts. One limitation of this study is that stockouts are not recorded but are “detected” from the sales data.

Finally, Anderson et al. (2006) conduct a large-scale field test with a national mail-order catalog firm and find that stockouts have an adverse impact on both the likelihood that a customer will place another order and the amount that the customer will spend on future orders (if any). They also find that a stockout on one item of an order increases the probability of customers canceling other items in that order, possibly because of the complimentary nature of many of the products sold by the firm, but also because of the shipping and other fixed costs associated with an order.

Our work follows the stream of research that analyzes historical behavioral data to examine the short- as well as the long-term effects of stockouts; however, our empirical study is performed on a wholesale instead of a retail environment.

**Collection and basic statistical analysis of the data**

The firm that provided the customer order and delivery data for our study was established as a retailer of ironware in 1922. Today, it is a wholesaler and distributor of hand tools, hardware, industrial tools and equipment, electric power tools, accessories for power tools, welding machines and accessories, agricultural implements, and other similar products. The firm sells products of many major European, Asian, and American tool manufacturers in a very competitive environment. The facilities of the firm include a large central warehouse that sells items to retailers and a local retail outlet that sells items directly to consumers. The sales department of the firm is staffed with twelve well-trained salespersons that travel in company owned cars to support customers throughout the country. The customers are retail shops.

Customers place their orders usually by toll-free phone or fax and sometimes by email, and ideally expect their orders to be met immediately. Each order typically contains several items in different quantities and at different prices and is handled by the salesperson who has been assigned to the customer that placed the order. The items of the order that are in stock are delivered to the customer usually on the next working day. Same-day delivery is possible
for orders that are placed before noon. The items that are out of stock are backordered. Some of the backordered items may be delivered at a later date or dates. Usually, an order is partially met in more than one delivery, and part of it may be cancelled.

The firm keeps a paper record of every order that is received, which includes the items that may eventually be cancelled from the order. For each order, it also keeps a record of the delivery dates and the items delivered on those dates. We were given limited access to these records, for the nine most important customers of the firm, for a period of four years that included 1043 working days. One of these customers, customer 5, is the local retail outlet of the firm, i.e., customer 5 belongs to the wholesaler.

From the records, we extracted the order and delivery information for each customer. To simplify the analysis of the data, we aggregated all the items in each order and expressed each order and its deliveries in terms of their monetary values. More specifically, for each order $i$ of each customer, we collected the following raw data:

- $a_i$: arrival date of the order;
- $d_i$: monetary value of the order that was initially placed, including the value of the items that were eventually cancelled from the order;
- $J_i$: number of deliveries of the order;
- $b_{ij}$: delivery date of the $j^{th}$ delivery of the order, $j = 1, \ldots, J_i$;
- $q_{ij}$: monetary value of the $j^{th}$ delivery of the order, $j = 1, \ldots, J_i$;
- $\kappa_{ij} = b_{ij} - a_i$: delay in number of working days between the arrival date of the order and the $j^{th}$ delivery date of the order, $j = 1, \ldots, J_i$.

As was mentioned above, our main goal is to examine if the customer service that the wholesaler provides to any particular order of a customer affects 1) the fill rate of that order, i.e., the fraction of the order that is eventually materialized, i.e., is not cancelled, and 2) the rate of future orders of the same customer. To this end, we defined a set of variables to be used as measures of the customer service level, the order fill rate, and the rate of future orders. More specifically, for each order $i$, we defined the following variables as measures of the customer service level and the order fill rate, and computed their values:

- $x_i = 1 - \sum_{j=1}^{J_i} q_{ij}/d_i$: fraction of the value of the order that was cancelled;
- $k_i = \kappa_{i,J_i}$: maximum delivery delay;
- $f_i = \sum_{j=1}^{J_i} \kappa_{ij} (q_{ij}/d_i) + \beta k_i x_i$: weighted sum of delivery delays plus a penalty term for the cancelled part of the order;
- $s_i = $ stockout occurrence indicator; $s_i = 0$, if $k_i \leq 1$, and $s_i = 1$, if $k_i > 1$. 


In the above expression for $f_i$, the summation term represents the weighted sum of the delivery delays, where the delay of each delivery is weighted by the fraction of the value of the order that was filled in that delivery. This term alone, however, does not account for the cancelled part of the order. To account for that part, we assigned to it an artificial delay whose role is analogous to that of the actual delay of a delivered part of the order; namely, the bigger the delay, the worse the customer service. To make this artificial delay weigh relatively heavily on $f_i$, since after all it is associated to a cancellation, we chose it to be equal to the maximum delivery delay, $k_i$, multiplied by a factor of $\beta$, where $\beta > 1$. Then, we multiplied the artificial delay with the fraction of the order that was cancelled and added the resulting product to the summation term in the expression for $f_i$. The results that we report in this paper are for $\beta = 2$. We should note however that when we tried several other values for $\beta$ between 1 and 2, the conclusions that we reached were qualitatively the same as those for $\beta = 2$, which we report in this paper.

For each order $i$, we also defined the following variables as measures of the rate of future orders, and computed their values:

- $e_i = a_{i+1} - a_i$: number of working days until the arrival of the next order;
- $h_i = d_{i+1}$: monetary value of the next order placed.

Finally, for each customer we defined the following variables:

- $N$: number of orders (observations) recorded;
- $M = \sum_{i=1}^{N} s_i$: number of stockout occurrences;
- $E_s = \frac{1}{M} \sum_{i=1}^{N} s_i e_i$: average number of working days until the arrival of the next order following a stockout;
- $E_n = \frac{1}{N-M} \sum_{i=1}^{N} (1-s_i)e_i$: average number of working days until the arrival of the next order following a non stockout;
- $D_s = \frac{1}{M} \sum_{i=1}^{N} s_i d_i$: average monetary value of the next order placed following a stockout;
- $D_n = \frac{1}{N-M} \sum_{i=1}^{N} (1-s_i)d_i$: average monetary value of the next order placed following a non stockout;

From the data that we collected for each customer, we computed the sample mean and coefficient of variation (CV) for all the variables. In addition, we used least-squares to fit the
order interarrival times, $e$, with Weibull distributions, which were found to fit the data fairly well, due to their flexibility. The results are shown in Table 1, where the “scale” and “shape” refer to the parameters of the best-fitting Weibull distribution.

| Table 1: Statistics of the order and delivery variables |
|---|---|---|---|---|---|---|---|---|---|
| | Customer | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| $N$ | 80 | 53 | 121 | 42 | 147 | 59 | 247 | 48 | 41 |
| $x$ Mean | 0.0310 | 0.0543 | 0.0453 | 0.0803 | 0.0447 | 0.0473 | 0.0180 | 0.0271 | 0.0351 |
| $x$ CV | 3.1807 | 1.5816 | 2.8148 | 1.4645 | 2.2196 | 1.7937 | 3.7844 | 3.6385 | 2.5932 |
| $k$ CV | 2.6324 | 1.1937 | 2.0283 | 1.0503 | 5.2273 | 1.9536 | 3.4418 | 1.4019 | 1.3330 |
| $f$ CV | 2.2602 | 1.1002 | 2.0763 | 0.9478 | 1.9906 | 1.1370 | 5.9746 | 1.8950 | 1.9711 |
| $e$ Mean | 8.4000 | 17.9434 | 5.9256 | 18.5952 | 4.7415 | 15.7966 | 2.8300 | 18.9167 | 18.6829 |
| $e$ CV | 2.6012 | 1.1002 | 2.0763 | 0.9478 | 1.9906 | 1.1370 | 5.9746 | 1.8950 | 1.9711 |
| $h$ Mean | 509.8670 | 1749.4500 | 443.0770 | 868.0060 | 181.8400 | 500.0200 | 76.3520 | 403.2890 | 890.0800 |
| $h$ CV | 509.8670 | 1749.4500 | 443.0770 | 868.0060 | 181.8400 | 500.0200 | 76.3520 | 403.2890 | 890.0800 |
| $M$ Mean | 21 | 38 | 43 | 35 | 30 | 29 | 27 | 29 | 25 |
| $M$ CV | 0.8279 | 0.9304 | 1.1447 | 0.7317 | 1.1420 | 0.6552 | 0.7363 | 0.9094 | 0.8939 |

From the sample means of the variables of each individual customer shown in Table 1, we can see that the customers exhibited different ordering behaviors in terms of the average frequency and the monetary value of their orders. As a result, they received different average levels of customer service, to which they responded correspondingly. More specifically, we observe the following behavioral patterns.

Customers with larger $\mu_e$ values, i.e., who on average order less frequently, tend to have larger $\mu_h$ values, i.e., tend to place larger orders, with the exception of one customer (customer 8), who places smaller orders relatively infrequently. The frequency with which a customer orders generally depends on his fixed ordering costs, which to a large extent include the transportation costs for receiving the items and are related to the customer’s distance from the supplier. This frequency, however, also depends on the sophistication of the customer. Customers that are more sophisticated tend to operate in a more “just-in-time” fashion, ordering smaller quantities more frequently.

Customers with larger $\mu_e$ values, i.e., who on average order less frequently, also tend to have larger $\mu_k$ and $\mu_f$ values, i.e., tend to face larger maximum and average delivery delays. This is most likely due to the fact that these customers can tolerate longer delays. Customers
who order more frequently, on the other hand, are more pressed to get the items that they request; therefore, they are less tolerant to long delays and do not wait too long before they switch to alternative sources for the missing items.

Customers with larger $\mu_h$ values, i.e., who on average place larger orders, tend to have larger $\mu_c$ values, i.e., tend to have larger cancellation percentages. This can be explained by the fact that the items demanded by a customer who places bigger orders less frequently are perhaps not that crucial to that customer, because they are based on a longer-term – and therefore relatively inaccurate – forecast of his requirements; hence, such a customer will more easily cancel his order for out-of-stock items, irrespectively of the estimated delivery delay for these items. The items demanded by a customer who places smaller orders more frequently, on the other hand, are more indispensible to that customer, because they are based on a shorter-term – hence, more accurate – forecast of his requirement; therefore he is more reluctant to drop them from his order.

From the sample CVs of the variables shown in Table 1, we observe that different variables exhibit different levels of variability. Using the classification that a random variables has low, moderate, or high variability, if its CV is smaller than 0.75, between 0.75 and 1.33, or greater than 1.33, respectively, we can see from the data that the number of days until the arrival of the next order, $e$, has low to moderate variability for all the customers. Similarly, the monetary value of the next order, $h$, has moderate variability for all the customers, except for one customer (customer 6) that exhibits low variability. On the other hand, all the variables that are related to customer service and to the customers’ immediate response to that service, i.e., $x$, $k$, and $f$, have moderate to high variability for all customers. The fact that the variables related to customer service exhibit higher variability than the variables related to customer demand is probably due to the fact that the firm’s supply process, which directly affects customer service, is more variable than the demand process. This is a well-known phenomenon in supply chain management which is often referred to as “bullwhip effect”.

From Table 1, we can also observe that the shape parameter of the Weibull distribution of the number of days until the next order arrival, $e$, is between 1 and 2 for all the customers. This implies that the distribution of $e$ is skewed to the left. It also means that the order interarrival times have an increasing and concave “hazard rate,” i.e., the longer the time since the last order arrival date, the larger the probability that the next order will arrive soon. This is natural, because as the time since the last order arrival date of any particular customer passes, this customer’s inventories are being depleted by his own customers (who are
consumers) and so the probability that he will soon place a replacement order increases. The fact that the shape parameter is greater than one for all the customers also means that the interarrival time distributions deviate from the exponential distribution, for which the shape parameter is one, although not dramatically, since for five out of nine customers, that parameter is below 1.2, and for the remaining four customers it is between 1.2 and 1.4.

Many analytical models in inventory management assume that the customer order interarrival times as well as the order sizes are independent random variables. To test the validity of this assumption on our data, we examined if there is any significant autocorrelation in that data. Lack of autocorrelation is necessary but not sufficient to show that successive observations of a random variable are independent. For all practical purposes, however, testing for the existence of significant autocorrelation should suffice as an indication of independence. Using (auto) regression analysis, we calculated the autocorrelation coefficients for lags ranging from 1 to 10, and we performed the Durbin-Watson test for addressing the significance of the lag – 1 autocorrelation, for the times between consecutive customer orders, \( e \), and the monetary values of each order, \( h \), for each customer. For all the \( e \) and \( h \) data, we found that the Durbin-Watson statistic is very close to 2, which means that the lag – 1 autocorrelation in the data is very small. We then addressed the significance of the lag – 1 autocorrelation with the Durbin-Watson test. The conclusion was that there is no significant (\( p < 0.01 \)) positive nor negative lag – 1 autocorrelation in any of the data; therefore, assuming independence appears valid for all practical purposes for both \( e \) and \( h \).

**Effect of customer service on present sales**

In the previous section, we conjectured that customers who order less frequently tend to place larger orders and tolerate longer delivery delays. At the same time, they tend to respond to stockouts with larger order cancellation percentages. To further explore this behavior, we investigated if there is any significant correlation between customer service and the order fill rate for each customer. More specifically, we examined if the maximum delivery delay, \( k \), which is a measure of customer service, is significantly correlated with the fraction of the value of the order that is cancelled, \( x \), where \( x \) is the complement of the order fill rate.

To investigate if there is any significant correlation between \( k \) and \( x \), we computed Spearman's correlation coefficient \( \rho \) which measures the rank-order association between two variables and works regardless of the distributions of the variables. Table 2 shows \( \rho \) with its one-tailed significance level \( p \) for variables \( k \) and \( x \), for each customer. Correlations that are
significant at a 0.05 level are marked with one asterisk, while those that are significant at a 0.01 level are marked with two asterisks.

Table 2: Spearman’s \( \rho \) correlation coefficient and corresponding one-tailed significance level \( p \) regarding the correlation between variables \( k \) and \( x \)

<table>
<thead>
<tr>
<th>Customer</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \rho )</td>
<td>0.1155</td>
<td>0.2206</td>
<td>0.4915**</td>
<td>0.0867</td>
<td>0.4133**</td>
<td>0.1532*</td>
<td>-0.0769</td>
<td>0.0903</td>
<td></td>
</tr>
<tr>
<td>( p )</td>
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<td>0.0000</td>
<td>0.2925</td>
<td>0.0000</td>
<td>0.0249</td>
<td>0.0082</td>
<td>0.3017</td>
<td>0.2873</td>
</tr>
</tbody>
</table>

From the results displayed in Table 2, we can see that for four out of nine customers, namely customers 3, 5, 6, and 7, there is a significant \( (p < 0.05) \) positive correlation between \( k \) and \( x \). The existence of these correlations implies that when customers 3, 5, 6, and 7, face larger delivery delays, they respond with larger order cancellation percentages.

For the remaining five customers, namely 1, 2, 4, 8, and 9, Spearman’s \( \rho \) coefficient is positive (except in the case of customer 8) but not significantly \( (p < 0.05) \) different from zero. For these customers, therefore, there is no significant evidence that the delivery delays affect the order fill rate.

The above analysis is a typical application of multiple hypothesis testing. Namely, for each customer \( i \) we tested the null hypothesis \( H_i: \) “\( k_i \) and \( x_i \) are not positively correlated,” against the alternative hypothesis \( \hat{H}_i: \) “\( k_i \) and \( x_i \) are positively correlated.” However, as is often noted in the multiple testing literature (e.g., see Westfall and Young 1993), performing many hypothesis tests may give rise to the “multiple testing problem,” which in our case can be stated as follows: the larger the number of customers we perform the test, the more likely we will find significant evidence that \( k \) and \( x \) is positively correlated for some of these customers, whereas in fact this significance may be due to chance. To tackle the multiple testing problem, and answer the question, “is the significance of the correlation between \( k \) and \( x \) real or is it due to chance?” we applied Holm’s (1979) stepdown method for controlling the family-wise error rate (FWE).

Holm’s method works as follows: Order the \( p \)-values as \( p_{(1)} \leq p_{(2)} \leq \ldots \leq p_{(N)} \), where \( N \) is the number of test-cases (in our case, customers) and let \( H_{(1)}, \ldots, H_{(N)} \) denote the corresponding hypotheses, where in our case \( H_{(i)}: \) “\( k_{(i)} \) and \( x_{(i)} \) are not correlated.” Apply the following sequentially rejective algorithm. If \( p_{(1)} > \alpha/N \), accept all hypotheses \( H_{(1)}, \ldots, H_{(N)} \) and stop, where \( \alpha \) is the preset FWE significance level; otherwise, reject \( H_{(1)} \) and continue. If continuing, then if \( p_{(2)} > \alpha/(N - 1) \), accept all hypotheses \( H_{(2)}, \ldots, H_{(N)} \) and stop; otherwise,
reject $H(2)$ and continue; and so on. In general, at the $n$th step, where $n = 1, \ldots, N$, if $p(n) > \alpha/(N - n + 1)$, accept all hypotheses $H(n), \ldots, H(N)$ and stop; otherwise, reject $H(n)$ and continue to the next step.

Applying Holm’s method to the data displayed in Table 2 leads to the following conclusion: For both $\alpha = 0.01$ and $\alpha = 0.05$:

- $k$ and $x$ are positively correlated for customers 3 and 5, and
- $k$ and $x$ are not correlated for the remaining customers.

We should keep in mind, however, that while the FWE is strongly protected using Holm’s step-down method, it is based on the Bonferroni probability inequality, and hence is conservative, i.e., it is more difficult to lead to a “reject $H_n$” conclusion. Note that if we apply Holm’s method for $\alpha = 0.06$, customer 7 will also join the list of customers for which we can accept the hypothesis that $k$ and $x$ are positively correlated.

To summarize, after applying Holm’s method, we can conservatively conclude that $k$ and $x$ are positively correlated for three customers at the 0.06 significance level. Looking at Table 1, these three customers, namely 3, 5, and 7, are the customers with the smallest mean $e$ values, i.e., they are those who on average order more frequently. In addition, they are those that have the smallest difference between their mean maximum delivery delay, $\mu_k$, and their mean order interarrival time, $\mu_e$. In other words, the maximum delivery delay $k$ is positively correlated with the cancellation percentage $x$ for the most frequent customers, whose mean maximum delivery delay is closest to their mean order interarrival time. This is most likely due to the fact that frequent customers are more pressed to receive the out-of-stock items. In general, they are reluctant to cancel these items, because they need them to fill their short-term – hence, relatively accurate – requirements, but at the same time, they will not hesitate to drop them from their order and look for them elsewhere, if the anticipated delivery time is greater that the time of their next order.

**Effect of customer service on future sales**

In the previous section, we concluded that stockouts had a significant adverse effect on the fill rate of customers who order frequently. The next question that we posed is whether stockouts also undermine future sales. To answer this question, we investigated if any of the variables that measure the magnitude of stockouts, which we call *independent* variables, were significantly correlated with the variables that measure the change in the rate of future customer orders, which we call *dependent* variables.
The independent variables that measure the magnitude of a stockout faced by any particular order $i$ of any particular customer are $x_i$, $k_i$, and $f_i$. The dependent variables that measure the change in the rate of future customer orders following order $i$ are $e_i$ and $h_i$. Intuition suggests that a drop in the rate of future customer orders may be affected not only by the most recent stockout experienced by a customer but by previous stockouts as well, although the effect of older stockouts on the drop in future customer demands should be less intense than the effect of more recent stockouts. In order to test the hypothesis that the drop – if any – in the rate of future customer orders due to the loss of customer goodwill is a phenomenon that is cumulative over time but at the same time customers are forgetting or forgiving as time passes, we introduced four new sets of variables, which were defined as the exponentially smoothed versions of the four original independent variables, $x_i$, $k_i$, and $f_i$. In each new variable, the magnitude of the stockout that the customer faced on his $i^{th}$ order is measured by weighing the current value as well as all the previous values of the respective variable with geometrically decreasing weights as we go back in time. More specifically, the exponentially smoothed versions of the independent variables were defined as follows:

$$X'_i = \gamma x_i + (1-\gamma)X'_{i+1},$$

$$K'_i = \gamma k_i + (1-\gamma)K'_{i+1},$$

$$F'_i = \gamma f_i + (1-\gamma)F'_{i+1},$$

where $\gamma$ is the smoothing factor. Note that as $\gamma$ tends to 1, more weight is being placed on the more recent value of the independent variable, whereas as $\gamma$ tends to 0, more weight is being placed on past values of the independent variable. In this study, we considered four values for $\gamma$, namely, 0.2, 0.4, 0.6, 0.8, and 1.

We computed Spearman's correlation coefficient $\rho$ with its one-tailed significance level $p$ for each pair of independent variables, $X'_i$, $K'_i$, and $F'_i$, and dependent variables, $e$ and $h$, for $\gamma = 0.2, 0.4, 0.6, 0.8, \text{ and } 1$. The results are shown in Tables 3 and 4, where the correlations that are significant at a 0.05 level are marked with one asterisk, while those that are significant at a 0.01 level are marked with two asterisks.

From the results displayed in Table 3, we can see that for eight out of nine customers at least one of the independent variables shows a significant ($p < 0.05$) correlation with dependent variable $e$. The only exception is customer 5, for whom no significant correlation is found. Also, from the results displayed in Table 4, we can see that for five out of nine customers, namely customers 3, 4, 6, 8, and 9, at least one of the independent variables shows a significant ($p < 0.05$) correlation with dependent variable $d$. Moreover, for the majority of the cases that show significant correlation between an independent and a dependent variable,
the corresponding correlation coefficient $\rho$ is below 0.4, indicating that this correlation is not too strong.

Table 3: Spearman’s $\rho$ correlation coefficient and corresponding one-tailed significance level $p$ regarding the correlation between each independent variable and variable $e$

<table>
<thead>
<tr>
<th>Ind. var.</th>
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<th>6</th>
<th>7</th>
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<th>9</th>
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</thead>
<tbody>
<tr>
<td>$X_{1.1}$</td>
<td>$\rho$ 0.0054 0.0453 0.2658** 0.0083 0.0208 -0.120 0.1647** 0.2768* 0.0859</td>
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<td></td>
<td>$p$ 0.4810 0.3738 0.0016 0.4792 0.4013 0.1814 0.0048 0.0284 0.2967</td>
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<tr>
<td>$X_{0.8}$</td>
<td>$\rho$ 0.0415 0.0234 0.2487** -0.0494 0.0079 -0.0852 0.0533 0.1464 0.1907</td>
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<td></td>
<td>$p$ 0.3575 0.4339 0.0030 0.3780 0.4622 0.2605 0.2023 0.1603 0.1161</td>
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<tr>
<td>$X_{0.6}$</td>
<td>$\rho$ 0.0422 0.1087 0.2305** -0.1573 0.0312 -0.0554 0.0257 0.1387 0.2027</td>
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<td>$p$ 0.3551 0.2193 0.0055 0.1599 0.3536 0.3385 0.3441 0.1735 0.1019</td>
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<tr>
<td>$X_{0.4}$</td>
<td>$\rho$ 0.0618 0.1708 0.1998* -0.2397 0.0497 -0.0185 -0.0196 0.1180 0.1852</td>
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<td></td>
<td>$p$ 0.2930 0.1107 0.014 0.0631 0.2752 0.4447 0.3796 0.2121 0.1231</td>
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<tr>
<td>$X_{0.2}$</td>
<td>$\rho$ 0.0886 0.1972 0.1836* -0.3830** 0.0985 0.0042 -0.1017 0.0558 0.1583</td>
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<td></td>
<td>$p$ 0.2173 0.0785 0.0219 0.0061 0.1177 0.4875 0.0555 0.3531 0.1615</td>
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<tr>
<td>$K_{1.1}$</td>
<td>$\rho$ 0.1904* 0.1200 0.1595* 0.1937 0.0888 0.3064** 0.2232** 0.2844* 0.2368</td>
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<td>$p$ 0.0454 0.1959 0.0403 0.1095 0.1424 0.0091 0.0002 0.0250 0.0680</td>
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<tr>
<td>$K_{0.8}$</td>
<td>$\rho$ 0.1932* 0.2198 0.1001 0.2625* 0.0840 0.3043** 0.1793** 0.1691 0.2638</td>
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<td>$p$ 0.0430 0.0569 0.1374 0.0465 0.1558 0.0096 0.0023 0.1253 0.0478</td>
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<tr>
<td>$K_{0.6}$</td>
<td>$\rho$ 0.2010* 0.2483* 0.1015 0.2782* 0.0897 0.2947* 0.1672** 0.158 0.2336</td>
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<td>$p$ 0.0369 0.0365 0.1341 0.0372 0.1399 0.0117 0.0042 0.1417 0.0708</td>
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<tr>
<td>$K_{0.4}$</td>
<td>$\rho$ 0.1597 0.2914* 0.1232 0.2943* 0.1104 0.2815* 0.1353* 0.1290 0.1702</td>
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<td></td>
<td>$p$ 0.0785 0.0171 0.0892 0.0293 0.0915 0.0154 0.0168 0.1911 0.1436</td>
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<tr>
<td>$K_{0.2}$</td>
<td>$\rho$ 0.1515 0.2369* 0.2044* 0.2762* 0.1321 0.2058 0.1281* 0.0859 0.0578</td>
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<td></td>
<td>$p$ 0.0899 0.0438 0.0122 0.0206 0.0554 0.0589 0.0222 0.2808 0.3598</td>
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<tr>
<td>$F_{1.1}$</td>
<td>$\rho$ 0.1126 0.1303 0.2606** 0.0959 0.0048 0.1765 0.2677** 0.2982* 0.1323</td>
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<td>$p$ 0.1599 0.1762 0.0019 0.2729 0.4768 0.0906 0.0000 0.0198 0.2047</td>
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<tr>
<td>$F_{0.8}$</td>
<td>$\rho$ 0.1264 0.1143 0.2561** 0.0724 0.0298 0.1920 0.1938** 0.2618* 0.2153</td>
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<td>$p$ 0.1320 0.2075 0.0023 0.3244 0.3601 0.0725 0.0011 0.0362 0.0882</td>
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<tr>
<td>$F_{0.6}$</td>
<td>$\rho$ 0.1423 0.1114 0.239** 0.0173 0.0333 0.2003 0.1410* 0.2296 0.2758</td>
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<td>$p$ 0.1040 0.2135 0.0041 0.4568 0.3446 0.0642 0.0134 0.0583 0.0404</td>
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<tr>
<td>$F_{0.4}$</td>
<td>$\rho$ 0.1422 0.1107 0.2439** -0.0411 0.0557 0.1442 0.0678 0.1683 0.3079</td>
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<td></td>
<td>$p$ 0.1041 0.2150 0.0035 0.3980 0.2515 0.1379 0.1441 0.1264 0.0251</td>
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<tr>
<td>$F_{0.2}$</td>
<td>$\rho$ 0.1637 0.0293 0.2139** -0.0315 0.0945 0.0719 -0.0103 0.1181 0.2961</td>
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<td></td>
<td>$p$ 0.0734 0.4176 0.0092 0.4216 0.1275 0.2942 0.4359 0.2120 0.0301</td>
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</table>

From the data in Table 3, we can see that for all but one cases which show a significant correlation between an independent variable and variable $e$, this correlation is positive. This is in line with intuition which suggests that the larger the value of the independent variable, the lower the service level, and hence the longer the time until the next order, $e$. The only case where a significant correlation coefficient is negative is the case of the coefficient
between \(X^{0.2}\) and \(e\), for customer 4. In fact, this coefficient has the largest absolute value (0.3830) among all coefficients. Its negative sign, however, is counter intuitive and raises the suspicion that its apparent significance may be due to chance.

Moreover, from the results shown in Table 4, for the cases which show a significant correlation between an independent variable and variable \(h\), this correlation is sometimes negative and sometimes positive. A negative correlation coefficient means that the lower the customer service level in a stockout situation, the smaller the monetary value of the order following the stockout. This type of behavior is also reported in Campo et al. (2003) and Anderson et al. (2006), who find that customers that experience stockouts, spend less money (i.e., place orders of smaller monetary value) following the stockouts, although in both these studies this effect is small. A positive correlation coefficient, on the other hand, means that
the lower the service level in a stockout situation, the larger the monetary value of the order following the stockout. This type of behavior is counter-intuitive. One possible explanation for it is that a customer who faces a stockout may delay his order following that stockout, because of the dissatisfaction, but when he returns, he orders a larger amount, because his requirements have increased in the mean time (assuming of course that he has not satisfying all of his requirements elsewhere). Nevertheless, this wavering behavior again raises the suspicion that the respective significance may be due to chance.

To answer the question “are the observed significances real or are they due to chance?” we applied again Holm’s stepdown method to the data shown in Tables 3 and 4. The conclusions are:

For $\alpha = 0.01$:
- Independent variables $F_1^1$ and $F_0^{0.8}$ are positively correlated with $e$ for customer 3,
- independent variables $K_1^1$, $F_1^1$, and $F_0^{0.8}$ are positively correlated with $e$ for customer 7, and
- none of the remaining independent variables is correlated with $e$.

For $\alpha = 0.05$:
- Independent variables $X_1^1$, $X_0^{0.8}$, $X_0^{0.6}$, $F_1^1$, $F_0^{0.8}$, $F_0^{0.6}$, and $F_0^{0.4}$ are positively correlated with $e$ for customer 3,
- independent variables $X_1^1$, $K_1^1$, $K_0^{0.8}$, $K_0^{0.6}$, $F_1^1$, and $F_0^{0.8}$ are positively correlated with $e$ for customer 7, and
- none of the remaining independent variables is correlated with $e$.

For both $\alpha = 0.01$ and $\alpha = 0.05$:
- none of the independent variables is correlated with $h$ for any customer.

To summarize, after applying Holm’s method, we can conservatively conclude that for customers 3 and 7, some of the independent variables measuring the magnitude of a stockout are positively correlated with the time until the next order following the stockout, $e$, at both the 0.01 and 0.05 significance levels. Moreover, for these two customers, wherever there is a significant correlation between an independent variable and the dependent variable $e$, the higher the value of the smoothing factor $\gamma$, the bigger the correlation coefficient. This suggests that wherever $e$ is significantly affected by a stockout, it is mostly affected by the most recent stockout than by previous stockouts. In fact, for $\gamma = 0.2$, no independent variable is correlated with $e$, for neither customer. This suggests that the adverse effect of a stockout on future demand is short-term.
We can also conservatively conclude that none of the independent variables measuring the magnitude of a stockout are correlated with the monetary value of the order following the stockout, \( h \), at either the 0.01 or the 0.05 significance level, for any customer. This means that, although some customers who experience a stockout may delay their next order following a stockout, none drop the monetary value of their next order. Earlier, we mentioned that Campo et al. (2003) and Anderson et al. (2006) observed that customers who experience stockouts, spend less money following the stockouts, although in both these studies this effect is small. One possible explanation about why we find no significant evidence that stockouts cause a reduction in the monetary value of future sales, whereas Campo et al. (2003) and Anderson et al. (2006) find such evidence is that in our study customers are retailers, whereas in the other two studies customers are consumers. A consumer may perhaps abstain from buying a superfluous item on his list (an item that he does not really need), if he perceives the customer service to be poor, whereas a retailer will rarely drop an item from his list, because his purchases are not driven by personal utility or desire but by the need to meet the demand of his own customers, who are consumers. Another difference between our study and the other two studies is the type of products sold to the customers.

In the previous section, we conservatively concluded that for the three most frequent customers, namely customers 3, 5, and 7, stockouts have a significant effect on the order fill rate. In this section, we conservatively concluded that for two of these customers, namely customers 3 and 7, stockouts also have a significant effect on the frequency but not on the monetary value of future orders and that this effect seems to be more short- than long-term. This is not true for customer 5. In fact, it can be seen from Table 3 that customer 5 is the only customer that shows no significant correlation, even before applying Holm’s stepdown method. A question that arises naturally is why do stockouts affect the order fill rate of customer 5 but do not affect his future demand? The answer is simple. As was already mentioned earlier, customer 5 is the only retailer who is actually owned by the wholesaler. Therefore, even though a stockout may force this customer to cancel the missing part of an order and look for it elsewhere, it does not affect his future loyalty to the wholesaler, neither in the long- nor in the short-term. In fact, it is interesting to note from Table 1, that customer 5 has the smallest absolute difference between mean interarrival time, \( \mu_e \), and maximum delivery delay, \( \mu_k \). This suggests that even when he cancels the missing part of an order, he does so just a little before he places his next order, i.e., “at the last moment”.

19
Summary and implications of results

In the previous sections, we reported results on the effects of stockouts on present and future sales from an empirical study of historical customer order and delivery data of a tool wholesaler and distributor. In this section we summarize our results and discuss some of their implications for OM researchers and practitioners.

Our analysis shows that customers who order less frequently tend to place larger orders and tolerate longer delivery delays. At the same time, they tend to respond to stockouts with larger order cancellation percentages, most likely because the out-of-stock items are not that indispensable to them, since their orders are based on longer-term – hence, less accurate – forecasts. This suggests that inventory control models in which order fill rates are assumed to depend on order frequencies may be a good representation of reality in environments similar to ours.

Our analysis also shows that the variables related to customer service exhibit higher variability than the variables related to customer demand. This is probably due to the fact that the firm’s supply process, which directly affects customer service, is more variable than the demand process. The elevated variability in customer service is to some extent due to the highly disruptive effect of stockouts. A better design of the stocking and reordering policy used by the company might help reduce some of this variability.

Another finding is that the customer order interarrival time distributions are skewed to the left and deviate from the exponential distribution although not dramatically. This does not mean that inventory control models assuming exponentially distributed interarrival times are necessarily inaccurate; however, such models should certainly be used with caution when the interarrival times deviate from the exponential distribution.

We also found that customer order interarrival times and monetary values are not autocorrelated, which for all practical purposes means that they are independent. This is good news for inventory control modelers, who often assume independently distributed demands.

Our main finding is that for customers who order frequently, stockouts do have an adverse effect on present and future sales. They have an adverse effect on present sales probably because frequent customers are more pressed to receive the out-of-stock items. They are reluctant to cancel these items, because they need them to fill their short-term – hence, relatively accurate – requirements, but at the same time, they do not wait long before they look for them elsewhere.

There are three possible reasons for why stockouts have an adverse effect on future sales for frequent customers.
The first reason is that when a frequent customer places an order, he has a more vivid memory of his previous orders and associated stockouts, simply because these orders are more recent. Our analysis shows, however, that even for frequent customers this memory seems to be short-term and does not affect long-term sales.

The second reason is that when a frequent customer is forced to demand the missing items of an order from an alternative supplier, the instant that he places his demand to that supplier is often very close to the instant that he is about to place his next order to the original wholesaler. In such a case, he may decide to skip placing his next order to the original wholesaler and instead place it to the alternative supplier along with his demand for the missing items, to save fixed order costs. Indeed, the evidence in Table 1 confirms that for frequent customers, the mean value of the maximum delivery delay, $\mu_k$, which should be related to the time that a customer decides to cancel the missing part of his order, is quite close to the mean interarrival time, $\mu_e$.

The third reason is that a frequent customer may operate in a more “just-in-time” manner than a less frequent customer, in which case he can be considered to be more flexible and sophisticated. Being more sophisticated, he is more sensitive and reactive to poor customer service on the part of the wholesaler.

There are several issues that we did not take into account in this study. We did not analyze in detail the items in each order. Also, we did not take into account factors for which we had no data, such as whether the customers accepted item substitution in case of a stockout, whether the firm offered a price discount for the out-of-stock items, whether the cancelled items of an order were purchased from an alternative wholesaler or were included in a subsequent order, etc. Future research should be directed towards including such details in the analysis.

**References**


