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# Effect of Traffic on Sales and Conversion Rates of Retail Stores

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Attracting shoppers to stores and converting the incoming traffic into sales profitably are vital for the financial health of retailers. In this paper, we use proprietary data pertaining to an apparel retailer to study the relationship between store traffic, labor, and sales performance. We decompose sales volume into conversion rate (defined as the ratio of number of transactions to traffic) and basket value (defined as the ratio of sales volume to number of transactions) and analyze the impact of traffic on sales and its components. We find that store sales volume exhibits diminishing returns to scale with respect to traffic, and labor moderates the impact of traffic on sales. For example, we find that for values of traffic and labor corresponding to the mean, increasing average traffic per hour by one unit increases average sales volume per hour by $9.97. Further, we find that the marginal returns to traffic increases from $10.00 to $11.32 when labor increases by one standard deviation. In addition, we find that the conversion rate declines with increasing traffic and a lower conversion rate is associated with a decrease in future traffic growth. Our study underscores the importance of in-store operations in driving the financial performance of retailers.

*Key words*: store performance; traffic variability; traffic uncertainty; store labor management; retail operations
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## 1. Introduction

The financial performance of a retailer relates to its ability to attract traffic into its stores and convert the incoming traffic into sales profitably. Thus, retailers invest heavily in marketing activities, to draw customers into their stores, and in store operations, to convert the traffic into profitable sales.

Retailers use different strategies to increase store traffic. They invest in prime real estate with desirable properties such as high foot traffic of targeted customer segments, convenience, and visibility. Once they determine a location, retailers drive store traffic in a variety of ways; these methods include spending on advertising; offering loss-leader products; and conducting various promotional events, such as offering discounts, getting celebrities like authors or sports people, and conducting workshops or seminars.

When customers visit the stores, retailers try to convert the traffic into sales profitably through several means. They ensure that the right product is available at the right place, at the right time, and at the right price (Fisher 1997). They invest in store labor to ensure that customers have a good shopping experience that encourages them to purchase and return to the store in the future. Some common elements of customer service include greeting customers upon store entry, aiding in the decision process by helping customers find the item they are looking for, providing product knowledge, suggesting alternatives, and providing expedited checkout.

Considerable empirical research examines the impact of different marketing activities in driving store traffic (e.g., Lam et al. 2001). However, little empirical evidence exists on the impact of traffic on store performance in the brick-and-mortar setting. Specifically, the relationships between store traffic characteristics—such as mean traffic, intraday traffic variability, and interday traffic variability—and store performance are unclear. Knowledge of these relationships is critical to retailers for the following reasons. First, tracking store traffic—and gaining an understanding of how traffic affects store performance—facilitates the development of labor planning and scheduling models for effective utilization of store labor, which is the second largest expense for retailers (Netessine et al. 2010). This understanding further helps retailers identify their "periods of potential," i.e., their key selling periods, and optimize their service levels not only by assigning the right number of associates to the selling floor but also having the best performing associates work during those key periods. Second, tracking traffic allows retailers to identify appropriate key performance indices to benchmark the performance of different stores. Traditional store performance metrics such as sales and profits do not provide the whole picture, as they do not reveal the sales potential of their stores or the ability of their stores to convert that potential into sales. Finally, the ability to forecast traffic and evaluate its impact on store performance can enable retailers to identify strategies to increase sales for each store and lead to better coordination between marketing activities and labor planning/scheduling activities.

In this paper, we investigate the relationships between store traffic characteristics, labor, and sales performance, measured as the number of transactions and sales volume, by collecting both hourly and daily traffic data from 41 stores of a women's apparel retail chain over a one-year period. In addition to studying the above traditional store performance measures, we also examine a metric called conversion rate, which is defined as the ratio of transactions to traffic. This measure appears to be growing in importance among retailers because of anecdotal evidence that an increase in conversion rate is positively associated with an increase in customer loyalty (Conroy and Bearse 2006). In this study, we test this claim by examining the relationship between conversion rate and future traffic growth.

Our research setup has several advantages. First, unlike previous research that was conducted in settings in which the conversion rate was close to 100% (e.g., Fisher et al. 2006, Netessine et al. 2010), the conversion rate of retail stores in our study exhibits considerable heterogeneity; it varies between 7% and 25% across stores and time. Consequently, we can study separately the relationship between traffic characteristics and the components of sales, namely, conversion rate and basket value, where basket value is defined as the dollars spent per transaction. Second, unlike several authors who have used the number of transactions as a proxy for store traffic, we use actual traffic data obtained from traffic counters installed in front of the stores. The traffic data are available at an hourly level that allows us to study the effects of interday traffic variability on store performance. Third, our panel data allow us to control for unobservable factors, such as corporate policy, product mix, and service levels that would be common across stores and may be time invariant. In addition, we utilize the heterogeneity in the locations of the 41 stores by separately collecting data on the locations' per capita income, weather, and competition to study the impact of these factors on store performance.

We report the following main findings. First, we report the impact of store traffic on sales performance. We distinguish the impact of store traffic on sales volume from its impact on the number of transactions. We find that sales volume and number of transactions are related to store traffic in an increasing concave function. Thus, store sales performance exhibits diminishing returns to scale with respect to traffic. For example, we find that for values of traffic and labor corresponding to the mean, increasing average traffic per hour by one unit, increases average sales volume per hour by $9.97. We also find that both intraday and interday traffic variability are associated with decreases in store sales performance.

Second, we find that store labor moderates the impact of traffic on store sales performance. In other words, the impact of traffic on store performance depends on the amount of labor that staffs the stores. For values of store labor corresponding to mean, mean minus one standard deviation, and mean plus one standard deviation, the marginal returns to traffic for the store with mean traffic are $10.00, $8.68, and $11.32, respectively. This finding implies that retailers need to carefully allocate their budget between marketing activities intended to drive store traffic and store labor, which is necessary to harvest the incoming traffic. In addition, we find that sales performance exhibits diminishing returns to labor. This relationship supports the idea proposed in Fisher et al. (2006) that reallocation of payroll budget across stores based on the marginal impact of labor on sales would yield an increase in sales.

Third, we find that conversion rate decreases nonlinearly with an increase in traffic. Also, we find that an increase in conversion rate is associated with an increase in future traffic growth. Thus, converting incoming traffic could potentially have long-term implications on retailers' store performance. Finally, we find that competition, per capita income, holidays, and macroeconomic conditions have significant explanatory power over store performance.

Our research contributes to the operations management literature in the following ways. Although a large body of literature in operations management investigates the role of inventory in managing demand, limited literature exists on how retailers can use labor to manage demand in the retail setting. The use of labor is a topic of emerging interest in operations management (Fisher et al. 2006, Ton 2009, van Donselaar et al. 2010, Netessine et al. 2010). Our study is, to the best of our knowledge, the first to show the moderating role of labor in the relationship between traffic and store sales performance. In addition, our paper is the first in operations management to use actual traffic data to characterize the relationship between traffic and store sales performance. Finally, demand uncertainty and variability are notions that have traditionally been of interest to the operations community; numerous analytical methods have been developed to manage them in different settings, such as inventory management and labor planning in call centers. By quantifying the negative impact of traffic variability on store performance, our study strengthens the need to develop analytical models and simulation methods to manage traffic variability in retail settings; it also provides empirical evidence on the various relationships that may guide the development of such analytical models.

Our results underline a number of contributions to retail practice. First, many retailers use metrics such as conversion rate, basket value, and sales per employee to measure performance and compensate employees. For instance, retailers such as The Limited and Donna Karan New York use conversion rate to compensate store associates (Kroll 2009). Our results justify the importance placed by retailers on this metric. However, the nonlinear relationships among traffic, labor, and conversion rate as shown in this paper imply that retailers need to be careful when applying this metric in measuring performance. Second, we show both the short- and long-term impacts of labor on store performance. In the short term, lower staffing levels are associated with lower conversion rate. In the long term, lower conversion rates are associated with lower traffic growth. As pointed out by Ton (2009) and Fisher and Raman (2010), retailers tend to reduce labor in their stores because they view it as a short-term expense. Our study demonstrates the importance for retailers to take into account both the short- and long-term impacts of labor before making their labor decisions, as myopic behavior might affect store performance over the long run. Third, our results highlight the importance of considering traffic uncertainty in labor planning. Most labor planning tools use a point forecast of traffic or sales to plan labor and thus ignore traffic uncertainty in their plans. This would lead to greater mismatches between store traffic and labor; such mismatches have been found to have a detrimental impact on store performance (Netessine et al. 2010).

## 2. Literature Review

The importance of store labor is underscored in the pioneering work of Raman et al. (2001), which focuses on the prevalence of execution issues in retail stores. These execution issues were classified as inventory record inaccuracy problems (DeHoratius and Raman 2008) and phantom stockouts (Ton and Raman 2010) and were found to impact retail store performance significantly. Fisher et al. (2006) studied the impact of execution issues on customer satisfaction and sales using survey data collected by a retailer. Their study finds that execution issues significantly impact both customer satisfaction and sales; they propose reallocation of labor across stores to address the execution issues and increase sales. Further proof of the importance of store labor is provided by Ton and Huckman (2008), who demonstrate an association between an increase in employee turnover and a decrease in profit margin and customer service. They find that this impact is moderated by the level of process conformance of the store. Finally, Ton (2009) shows that an increase in store labor is associated with higher profits through the impact on conformance quality but not on service quality. Our paper is similar to the above papers in examining store labor, but it differs from them in that it studies labor in conjunction with traffic, an important variable that was missing in the previous studies.

Recent work by Netessine et al. (2010) examines the impact of labor planning and labor execution on store performance. Netessine et al. (2010) associate matching store labor to traffic with greater basket values and suggest that better labor scheduling and execution would lead to better performance. Though their study does not possess traffic data, it uses monthly data on the number of transactions as a proxy for traffic, finding that conversion rate is close to 100% in its setting. Our study complements theirs and also provides new insights. First, we use actual traffic data at a daily level for our analysis. This level of granularity would significantly mitigate the aggregation bias that has been commonly found in aggregate data analysis (Blundell et al. 1993). Second, our results suggest that traffic variability could be an important driver of the mismatch between store labor and traffic observed by Netessine et al. (2010). So managing traffic variability is an important step toward achieving a good match between store labor and traffic. Attaining such a match may entail the use not only of better planning algorithms but also of introspection on the part of the retailers to determine if any of their actions are increasing traffic variability. Finally, because the conversion rate is not 100% in our setting, we are able to show that traffic variability also impacts conversion rate for retailers, thus furthering the findings of Netessine et al. (2010).

Next, we briefly review the marketing literature that treats store traffic as a traditional variable of interest. In contrast to our paper, most studies treat store traffic as a dependent variable and study the impact of marketing activities such as advertisements and price promotions on store traffic. Because of the lack of traffic data, most of those studies use the number of transactions as a proxy for store traffic (e.g., Walters and Rinne 1986, Walters and MacKenzie 1988). One paper that uses actual store traffic data is Lam et al. (2001); this study assesses the effectiveness of different promotional activities on store traffic, conversion rate, basket value, number of transactions, and sales volume. Lam et al. (2001) find that the effects of promotions on store performance can vary, depending on the type of promotion employed. Our paper differs from Lam et al. (2001) in both motivation and methodology. Lam et al. (2001) use traffic as a dependent variable, but we are interested in studying the impact of traffic on sales performance. Also, their study ignores store labor and traffic variability, which we identify as important factors that affect store sales performance. An earlier paper by Lam et al. (1998) uses store traffic data to study labor scheduling. That paper uses traffic data from one store to show that the relationship between traffic and sales volume is actually nonlinear. Our paper adds to this evidence by using data from a panel of 41 stores; in addition, we show the moderating role of labor and the impact of traffic variability on store performance, which are factors that Lam et al. (1998) do not examine.

Another body of research relevant to our work focuses on conversion rate for online retailers. Even though online retailing is a very recent phenomenon compared to brick-and-mortar retailing, there have been far more studies on online conversion rates than on conversion rate in the brick-and-mortar setting. These studies examined the influence of website design on online conversion rate (e.g., Geissler 2001, Lohse and Spiller 1999, Swaminathan et al. 1999, Mummalaneni 2005) and predicting conversion rates using clickstream data (e.g., Moe and Fader 2004, Moe et al. 2002). By identifying drivers of online conversion rates, these papers aim to improve performance of online retailers. The absence of traffic data has stymied research in similar topics in the brick-and-mortar setting. However, recent technological advances have enabled retailers to collect store traffic data, and our study is the first in operations management to examine factors that drive brick-and-mortar conversion rates.

## 3. Hypotheses

In this section, we develop hypotheses to relate store sales performance to traffic characteristics and labor. Retailers spend heavily to attract traffic into their stores. In 2009 alone, U.S. retailers invested about $17.2 billion in advertisements (Vranica 2009). To understand the return on investment of their marketing expenditure, it is not only essential to track how the marketing expenditure translates into store traffic, as studied by many researchers in the marketing literature, but also to examine how the store traffic is eventually converted into sales over the short and long terms. Thus, we derive hypotheses related to the effect of traffic on sales and conversion rate and the effect of conversion rate on future traffic growth. Motivation for our hypotheses is based on academic literature as well as on practice.

First, we predict a concave relationship between traffic and sales performance. We might expect an increase in traffic to lead to an increase in sales because higher traffic provides more opportunities for sales conversion. However, we expect a nonlinear relationship between traffic and sales because of the decline in service quality. Quality of service delivered to customers is a critical driver of retail success (Zeithaml et al. 1996). Parasuraman et al. (1988) identify responsiveness or the ability to provide prompt service as a critical factor driving the quality of service to customers. As store traffic increases, we expect responsiveness to decline within the store for several reasons. First, the store associates may be engaged with other customers who need assistance, so other customers may need to wait to get the help of store associates to find a product or get product knowledge. Second, retail stores have certain physical limitations such as the number of checkout counters and dressing rooms. So as traffic increases, the waiting time in front of the checkout counter and dressing rooms could increase as well. From queueing theory, we know that waiting time increases in a convex fashion with traffic, all else being constant. Larson (1987) provides a number of examples where the disutility of waiting increases nonlinearly with waiting time. Therefore, we expect an increase in store traffic, for a given level of labor, to lead to an increase in sales at a diminishing rate as incidences of balking and reneging will increase because of the decline in service quality.

Prior research suggests that congested stores may negatively impact the shopping experience of customers, resulting in fewer purchases. Studies of crowded stores have found that customers feel disoriented (Dion 1999), less satisfied (Eroglu and Machleit 1990), more stressed, and tenser (Langer and Saegert 1977). Negative feelings caused by in-store crowding have been found to translate into lower patronage for retail stores (e.g., Eroglu and Machleit 1990). Another study found that in overcrowded stores potential buyers may even deviate from their planned shopping experience by spending less money than planned or even leaving without making a purchase (Harrell et al. 1980). Finally, crowding in retail environments could also affect the performance of the sales associates who interact with the dissatisfied and/or aggressive customers (Lepore 1994), which has implications for the overall store performance.

Thus, we propose the following hypothesis:

Hypothesis 1. *The relationship between traffic and store sales performance is given by an increasing concave function.*

Next, we argue that store labor moderates the impact of traffic on store sales performance. Fisher et al. (2006), Ton (2009), and Netessine et al. (2010)

find that an increase in store labor is associated with a positive financial performance. One of the reasons for the increase in store performance relates to customer satisfaction, which is found to increase when customers experience good in-store customer service (e.g., Gómez et al. 2004). Sulek et al. (1995) show that customer service interventions result in greater customer satisfaction and improved sales volume. Such customer service interventions would depend on the availability of a sufficient number of store associates to interact with the incoming traffic. Thus we expect the impact of traffic on store sales would increase with increased store labor. This argument is consistent with queueing theory, which shows that waiting time in a system decreases with the number of servers. Reduction in waiting time would lead to less reneging and balking and consequently higher sales. Therefore, we expect the marginal impact of traffic on store sales performance to be positively associated with the level of store labor, leading to our next hypothesis:

Hypothesis 2. *The greater the level of store labor, the greater the positive impact of store traffic on store sales performance.*

Next, we consider the relationship between interday traffic variability and intraday traffic variability on store sales performance. We argue that both types of variabilities increase the difficulty in matching labor supply with labor demand. Labor mismatches could result in periods when customers may face lower service level, resulting in a decrease in sales.

The typical labor planning process for retail stores proceeds in two steps. The first step involves forecasting the amount of labor required in a store during a certain period. The second step involves scheduling labor based on this forecasted labor requirement and assessing employee availability after taking into account constraints such as minimum/maximum working hours, distribution of skills, preferred work schedules, etc. (Quan 2004).

Stores with higher interday traffic variability may be facing higher traffic uncertainty. This results in large errors when forecasting labor requirements for these stores. Such large forecast errors would result in large mismatches between store labor required to manage in-store customers and actual store labor present in the store. When required store labor exceeds actual store labor, customer service within the store would decline, resulting in fewer customer purchases.

Increased intraday traffic variability affects sales for the following reasons. For a given level of average daily traffic and staffing, queueing theory predicts that an increase in arrival variability would be associated with an increase in the expected waiting time at the queue (Kingman 1966). Because customers are sensitive to response times, high levels of intraday traffic variability would result in abandonment and reneging, leading to lower sales performance. Increased intraday traffic variability could also cause an increase in difficulties in scheduling labor. Labor scheduling is a complex task that requires matching supply of available store labor with planned labor. Store labor usually comprises full-time employees, part-time employees, and temporary workers. These employees may be available at different times of the day for different durations, rather than following a standard eight-hour work schedule. Possible further complications include different skill sets of the employees, minimum staffing requirements, overtime costs, wages, budget constraints, vacations, leaves, etc., that need to be taken into account when scheduling employees. Therefore, as the variability in intraday traffic increases, it will become more difficult for the retailer to schedule daily labor for different hours of the day, which may result in over- and understaffing at different hours of the day.

Therefore, we hypothesize the following:

Hypothesis 3A. *The greater the interday traffic variability, the lower the store sales performance.*

Hypothesis 3B. *The greater the intraday traffic variability, the lower the store sales performance.*

Next, we discuss the relationship between traffic and conversion rates. We expect that an increase in traffic would lead to greater reneging and balking because of declining service quality. This would result in lower conversion rates with increasing traffic. Therefore, we hypothesize that

Hypothesis 4A. *Increased store traffic is associated with a decrease in conversion rate.*

Finally, we discuss the relationship between conversion rate and future traffic growth. Conversion rate reflects not only the effectiveness of in-store logistics but also customer satisfaction. In particular, an increase in conversion rate can be treated as a signal of increased customer satisfaction for the following reasons. First, as discussed earlier, anecdotal evidence suggests that an increase in conversion rate is associated with an increase in customer loyalty. Second, an increase in conversion rate implies that more customers are purchasing, suggesting an increase in customer satisfaction with the retailer. Increased customer satisfaction, in contrast, has been found to be associated with repeat purchases, customer retention, and positive word-of-mouth communications (Athanassopoulos et al. 2001, Ranaweera and Prabhu 2003). All the above effects are expected to result in attracting more traffic into the stores. Hence, we hypothesize:

Hypothesis 4B. *An increase in conversion rate is associated with an increase in future traffic growth.*

## 4. Data and Methodology

We test our hypotheses using both proprietary and secondary data. We next present our data sources, followed by a description of the variables (dependent, independent, and controls) we use in our study.

### 4.1. Data Sources

We obtain store-level data for a large retail chain provided under conditions of nondisclosure and anonymity. We refer to this retail chain as "Alpha" in this paper. Alpha is a women's apparel retail chain that sells affordable luxury products. Its target customers are 21- to 35-year-old women, and its products span career, evening, and casual. Retailer Alpha operates more than 200 stores in 35 states in the United States, Puerto Rico, the U.S. Virgin Islands, and Canada as of July 2008. The retailer also sells online and through catalogs. Most of the retailer's stores are located in regional shopping centers, and some of them are present in freestanding street locations. The study period was from January 1, 2007 to December 31, 2007.

Retailer Alpha has a software tool to perform in-store labor allocation. However, store managers can override the labor allocation decisions of this tool, as they are ultimately responsible for payroll expenses because their bonuses are tied to store profits. Interviews revealed that stores schedule labor based on anticipated traffic.

We obtain the following data for the year 2007 for retailer Alpha: (i) financial data (i.e., number of transactions and store sales volume); (ii) labor data (i.e., employee hours); and (iii) traffic data. The retailer used traffic counters installed at the entrances of the stores to record the number of visitors to the store. Such traffic counters were installed in 60 of its stores located in the United States during our study period. The traffic counters use an advanced on-board video sensor with high-speed processing components to unobtrusively track customers' movements. This technology features the ability to distinguish between incoming and outgoing shopper traffic; count side-by-side traffic and groups of people; and differentiate between adults and children, while not counting shopping carts or strollers. This technology can also adjust to differing levels of light in the store; can time stamp each record, enabling the breakdown of data to any desired time increment; and can prevent certain types of counting errors. For example, customers would need to enter through fields installed at a certain distance from each entrance of the store for their traffic to be included in the counts.

The retailer has purchased this advanced traffic counting system from a third party that guarantees at least 95% accuracy of performance against real traffic entering and exiting a store. The third party follows a three-step process to ensure such accuracy in performance. First, the third party gathers the required information for each location, including store layout, entrances, and reporting needs. A group of technical experts is sent on site to do the installation. Second, once installed, the traffic counters must be configured to the individual traffic patterns of each store. Third, the configuration must be validated. The validation process ensures that a store's traffic data are not released for customer use until it meets the third party's contractual criteria for accuracy, which is usually in the 96%–98% range.

In addition to the above data, we collect additional data by accessing the website of the mall where each store is located. We record all the stores in the mall directory and use the count as a proxy for competition. Out of 60 stores, 5 stores are located in freestanding street locations and 5 in malls that did not have a working website. Moreover, there were 9 stores for which we did not have complete information for the entire year. Those stores either opened during that year or did not install traffic counters at the beginning of the year. To overcome this problem, we discard data from all the above 19 stores and focus only on those stores for which we could obtain complete information with respect to the above variables. Our final sample has data from 41 stores all located in malls/shopping centers and belonging to the same retail format. Finally, we collect the hours of operation by calling these stores directly.

We also collect data on the daily average temperature of each store location to test whether customer purchasing behavior is affected by weather. These data are obtained from the U.S. National Climatic Data Center in Asheville, North Carolina. The center archives data from the National Oceanic and Atmospheric Administration, a scientific agency within the U.S. Department of Commerce that studies the conditions of the oceans and the atmosphere. These data are accessible online; the administration's website provides different search capabilities for locating weather stations by city, zip code, state, and county. Each weather station has archived data on certain aspects of weather covering a specific time period. We identify weather stations, searching by zip code. As we were unable to identify a weather station for five zip codes, we used the closest station within 20 miles in these instances.

To control for economic conditions, we collect data on the Dow Jones Industrial Average using the Wharton Research Data Services. We use a five-day moving average for those days when the stock market was closed. We also obtain demographic data for the population in each store location, using U.S. Census data. We collect averages on median household income and per capita income for the year 2007 by location. The above variables are highly correlated; hence, we only use per capita income in our analysis.

### 4.2. Dependent Variable

To test Hypotheses 1–3 we measure sales performance for store $i$ on day $t$ in two different ways: sales volume in dollars ($SALES_{it}$) and the number of transactions that occur in the store ($TRANS_{it}$). We find that the store business hours vary across stores as well as within stores. To avoid the spurious correlation that could arise between our variables as a result of systematic differences in business hours, we divide $TRANS_{it}$ and $SALES_{it}$ by the regular business hours of each store on each day of the week to obtain average number of transactions per hour and average sales volume per hour. We denote these variables as $ATRANS_{it}$ and $ASALES_{it}$.

In Hypothesis 4A, our dependent variable is conversion rate ($CR_{it}$), which is calculated as follows: $CR_{it} = TRANS_{it}/TRAF_{it}$, where $TRAF_{it}$ is the total traffic in store $i$ on day $t$. In Hypothesis 4B, our dependent variable is future traffic growth. We measure it as the growth in average traffic for a given store $i$ in period $p$ (where $p$ denotes weeks and months in our analysis) and calculate it as follows: $\overline{TRAF\ GROWTH}_{ip} \equiv \overline{TRAF}_{ip}/\overline{TRAF}_{i,\,p-1}$. An alternate definition of traffic growth is the following: $\overline{TRAF\ GROWTH}_{ip} \equiv (\overline{TRAF}_{ip} - \overline{TRAF}_{i,\,p-1})/\overline{TRAF}_{i,\,p-1}$. We use the alternate definition to test the robustness of our findings. Finally, we calculate basket value in the following way: $BV_{it} = SALES_{it}/TRANS_{it}$.

### 4.3. Independent Variables

We divide traffic per day ($TRAF_{it}$) and labor hours per day ($LBR_{it}$) by the store business hours to obtain average traffic per hour ($ATRAF_{it}$) and average labor hours per hour ($ALBR_{it}$) on day $t$ for store $i$, for the same reason cited previously. Next, we obtain intraday traffic variability using hourly traffic data as follows: $TRAFVAR_{it} = \sigma_{it}/\mu_{it}$.

Here, $TRAFVAR_{it}$ denotes the coefficient of variation of traffic for store $i$ on day $t$; $\sigma_{it}$ and $\mu_{it}$ denote the standard deviation and mean of hourly traffic on day $t$ for store $i$, respectively. Let $h$ denote the index for store operating hours within a day and $H_{it}$ be the total number of operating hours for store $i$ on day $t$. Then,

$$\mu_{it} = \frac{\sum_{h=1}^{H_{it}} TRAF_{ith}}{H_{it}} \quad \forall\, i, t \quad \text{and}$$

$$\sigma_{it} = \sqrt{\frac{\sum_{h=1}^{H_{it}} (TRAF_{ith} - \mu_{it})^2}{H_{it} - 1}} \quad \forall\, i, t.$$

Next, we define interday traffic variability in the following way. First, we note that interday traffic variability arises because of seasonality of traffic as well as uncertainty. Store traffic exhibits strong seasonality based on day of the week, month, and holidays. Such seasonality can be anticipated ex ante and may be addressed through labor planning. Hence, we wish to create a model that removes the effect of seasonality, leaving behind residual uncertainty. We model traffic as an autoregressive process and add dummies for month, days of the week, and holidays. The lag length of this autoregressive process is selected by choosing the model across various lagged specifications that yields the lowest Akaike information criterion (AIC). The AIC is calculated as follows:

$$\log\left(\frac{SSR(\kappa)}{n}\right) + (\kappa + 1)\left(\frac{2}{n}\right),$$

where $SSR(\kappa)$ is the sum of squared residuals for the autoregression with $\kappa$ lags and $n$ is the number of observations.

To select the lag length $\kappa$, we start with a maximum lag of 7 and decrease it gradually to the appropriate lag until the AIC is minimized. We repeat the above approach for each store to identify the appropriate lag length. We find that in 40 stores (out of 41) the AIC estimate of the lag length is 7. In addition, we also looked at other information criteria such as the Schwartz criterion and the Hannan–Quinn information criterion, and the results are consistent. Therefore, we choose an order of 7 in our traffic autoregressive model and obtain the following model:

$$TRAF_{it} = b_{i0} + \sum_{l=1}^{7} b_{il} TRAF_{i,\,t-l} + b_{i8}\delta_h + b_{i9}\delta_m + b_{i10}\delta_d + \varepsilon_{it}.$$

Here, $\delta_h$ denotes holiday dummies, $\delta_m$ denotes monthly dummies, and $\delta_d$ denotes dummies for days of the week. Such an additive model allows us to estimate the uncertainty in traffic ($TRAFUNC_i$) using the uncertainty in the residuals in the following way: $TRAFUNC_i \equiv \mathrm{sd}(\varepsilon_{it}/TRAF_{it})$, where $\mathrm{sd}(\cdot)$ denotes the standard deviation. We estimate the regression coefficients $b_{i0} - b_{i10}$ using ordinary least squares.

Our approach of measuring interday traffic variability is similar in spirit to that of Rumyantsev and Netessine (2007), who use residuals from a quarterly sales volume equation to estimate demand uncertainty. We use interday traffic variability as a proxy for traffic uncertainty. To further test the robustness of our results, we measure interday traffic variability using models with different numbers of traffic lags. We describe these models in the sensitivity analysis section.

We are motivated by practice to measure labor-traffic mismatch as the ratio of traffic to labor. This ratio is used by many workforce management companies like ShopperTrak and SMS (St. Michael's Strategies) as a proxy for service level. An increase in this ratio indicates a decline in service level caused by greater mismatches between traffic and labor. We obtain labor-traffic mismatch on a given day based on the average ratio of traffic to labor for different hours of that day. That is,

$$MISMATCH_{it} = \frac{\sum_{h=1}^{H_{it}} TRAF_{ith}/LBR_{ith}}{H_{it}} \quad \forall\, i, t.$$

### 4.4. Control Variables

We construct our control variables based on both data availability and a framework used by Lam et al. (2001). We next describe the controls we use for our analysis. First, the sales performance of stores would depend on location-specific factors such as demographics and competition. We control for these two factors through use of per capita income ($PCI_i$) and the number of other stores in the mall, which is used as a proxy for competition ($COMP_i$). Second, store performance is also affected by store promotions (Walters and Rinne 1986, Walters and MacKenzie 1988, Lam et al. 2001). We could not obtain information regarding Alpha's promotional activities. As retailers typically run promotions in advance of holidays, we use holidays as a proxy for price promotions. We create a dummy variable HOLIDAYS ($\delta_h$) that is set to one up to three days before major holidays, such as the Christmas season (December 23–31), Easter, Memorial Day, Independence Day, Labor Day, Martin Luther King Day, Mother's Day, Veterans Day, and Thanksgiving Day. In addition, the three days after Thanksgiving are also classified as HOLIDAYS with $\delta_h = 1$.

Seasonality could also affect store performance. We control for seasonality by introducing monthly dummies. Because we have only one year of data, our monthly dummies would be unable to distinguish any firm-level factors that impact all stores at the same time from seasonal variations in performance. We performed hierarchical cluster analysis and found that traffic, sales, and conversion rate were similar for Monday–Thursday and for Friday–Sunday. So we used corresponding dummy variables in our regressions. We also tried other combinations of daily dummy variables and obtained similar results.

Next, positing that store sales performance would depend on the prevailing national macroeconomic conditions, we use the Dow Jones Industrial Average as a proxy for the macroeconomic conditions. Store sales performance on a given day could also depend on weather conditions on that day. Lam et al. (2001) use daily temperature as a control on weather conditions and treat it as a categorical variable. We adopt the approach of Lam et al. (2001) and create four dummy variables to capture the following daily temperature ranges: (i) <40 °F, (ii) 40–60 °F, (iii) 60–85 °F, and (iv) >85 °F.

We trim our data by excluding extreme values to obtain more robust statistics and estimators. We remove all the data below the 1st percentile and above the 99th percentile. We perform all further analysis on this data set.

We rescale the independent variables and controls so they could have similar scale. We divide $DJI_t$ and $PCI_i$ by $10^5$ and $COMP_i$ by $10^3$. We divide $ATRANS_{it}$, $ASALES_{it}$, and $BV_{it}$ by 10, $10^3$, and $10^2$, respectively. To distinguish our transformed/rescaled variables from the raw variables we use the letter $A$, which stands for adjusted, before the variables' names.

Table 1 describes the variables that we use, and Table 2 provides the descriptive statistics for all variables. We use subscript $i$, ranging from 1 to 41, to denote each store; we use subscript $t$, ranging from 1 to 365, to denote each time period. The average number of transactions per day in the retail chain is 97, average sales volume is \$8,919, and the average labor-hours per day is 56. The average values of conversion rate and basket value in our sample are 0.14 and \$90, respectively. In other words, a random customer walking into the store is expected to purchase \$12.60 worth of goods. Tables 3 and 4 present the correlations among mean-centered longitudinal and cross-sectional variables, respectively.

**Table 1 Variable Definition**

| Variable | Description |
|---|---|
| $TRAF_{it}$ | Total number of customers who entered store $i$ on day $t$ |
| $ATRAF_{it}$ | Average number of customers who entered per hour store $i$ on day $t$ |
| $SALES_{it}$ | Sales volume for store $i$ on day $t$ |
| $ASALES_{it}$ | Average sales volume per hour for store $i$ on day $t$ |
| $TRANS_{it}$ | Number of customer transactions at store $i$ on day $t$ |
| $ATRANS_{it}$ | Average number of transactions per hour for store $i$ on day $t$ |
| $CR_{it}$ | Proportion of customers who made a transaction at store $i$ on day $t$ |
| $BV_{it}$ | Value in U.S. dollars of customers' shopping basket at store $i$ on day $t$ |
| $LBR_{it}$ | Total number of employee hours reported at store $i$ on day $t$ |
| $ALBR_{it}$ | Average no. of employee hours per hour reported at store $i$ on day $t$ |
| $COMP_i$ | Total number of stores in the mall where store $i$ is located |
| $TEMP_{it}$ | Daily temperature for store location $i$ |
| $DJI_t$ | Dow Jones Industrial Average on day $t$ |
| $PCI_i$ | Per capita income for store location $i$ |
| $TRAFUNC_i$ | Average interday traffic variability for store location $i$ |
| $TRAFVAR_{it}$ | Intraday traffic variability for store location $i$ on day $t$ |
| $MISMATCH_{it}$ | Labor-traffic mismatch for store location $i$ on day $t$ |
| $\overline{TRAF\ GROWTH}_{ip}$ | Growth in average traffic for store location $i$ in period $p$ |
| $\overline{CR}_{i,p-l}$ | Average conversion rate for store location $i$ in period $p-l$ |

**Table 2 Summary Statistics of the Variables**

| Variable name | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|
| Raw variables | | | | |
| Longitudinal variables | | | | |
| $TRAF_{it}$ | 724 | 365 | 209 | 2,309 |
| $TRAFVAR_{it}$ | 0.642 | 0.162 | 0.269 | 1.066 |
| $MISMATCH_{it}$ | 15.382 | 7.220 | 3.579 | 123.333 |
| $CR_{it}$ | 0.139 | 0.032 | 0.071 | 0.252 |
| $BV_{it}$ | 90 | 22 | 39 | 159 |
| $TRANS_{it}$ | 97 | 45 | 29 | 280 |
| $SALES_{it}$ | 8,919 | 5,117 | 1,413 | 38,056 |
| $LBR_{it}$ | 56 | 19 | 24 | 122 |
| $OPER\ HRS_{it}$ | 11 | 1 | 6 | 14 |
| $TEMP_{it}$ | 64 | 15 | 18 | 93 |
| $DJI_t$ | 13,186 | 505 | 12,128 | 14,086 |
| Cross-sectional variables | | | | |
| $PCI_i$ | 36,092 | 19,359 | 12,763 | 92,940 |
| $COMP_i$ | 171 | 47 | 95 | 313 |
| $TRAFUNC_i$ | 0.165 | 0.032 | 0.109 | 0.264 |
| Transformed/rescaled variables | | | | |
| $ATRAF_{it}$ | 70.377 | 36.516 | 19.000 | 225.833 |
| $ABV_{it}$ | 0.901 | 0.217 | 0.394 | 1.592 |
| $ATRANS_{it}$ | 0.937 | 0.442 | 0.258 | 2.738 |
| $ASALES_{it}$ | 0.860 | 0.490 | 0.155 | 3.143 |
| $ADJI_t$ | 0.132 | 0.005 | 0.121 | 0.141 |
| $APCI_i$ | 0.361 | 0.194 | 0.128 | 0.929 |
| $ACOMP_i$ | 0.171 | 0.047 | 0.095 | 0.313 |

### 4.5. Model Specification and Estimation Methodology

Our hypotheses involve testing both time-variant and time-invariant factors. Similarly, we wish to control for both time-variant and time-invariant factors in our model. Hence, we choose a model specification that accommodates these aspects of our analysis.

We explain our modeling approach by means of a two-stage method (Fitzmaurice et al. 2004). In the first stage, we relate the average sales per hour for store $i$ on day $t$ to time-variant factors such as traffic characteristics and labor, as shown below.

$$\begin{aligned} ASALES_{it} = {} & \vartheta_0 + \vartheta_i + \vartheta_1 ATRAF_{it} + \vartheta_2 ATRAF_{it}^2 \\ & + \vartheta_3 ALBR_{it} \times ATRAF_{it} \\ & + \vartheta_4 ALBR_{it} \times ATRAF_{it}^2 + \vartheta_5 TRAFVAR_{it} \\ & + \vartheta_6 ALBR_{it} + \vartheta_7 ALBR_{it}^2 + \vartheta_8 W_{it} + \xi_{it}. \quad (1a) \end{aligned}$$

**Table 4 Correlations Among Cross-Sectional Variables**

| | 1 | 2 | 3 |
|---|---|---|---|
| 1. $TRAFUNC_i$ | 1 | | |
| 2. $APCI_i$ | 0.0246 | 1 | |
| 3. $ACOMP_i$ | −0.0249 | −0.0001 | 1 |

*Note.* For every pair of variables, the table provides the Pearson's correlation coefficient and its $p$-value for the hypothesis $H_1$: $|\rho| \neq 0$.

Here $\vartheta_i$ refers to a parameter specific to the $i$th store. This store-specific fixed effect is critical to our model, as it eliminates bias that might otherwise occur from factors such as store size and unobservable manager skills that drive both store labor and sales. For example, Siebert and Zubanov (2010) find that able managers could achieve up to 13.9% higher sales per worker than less skilled managers. $W_{it}$ is a column vector of control variables that includes time dummies to control for time-specific effects, temperature dummies, and a lagged dependent variable, as it is a good predictor of future sales.

We test Hypothesis 1 using estimates of coefficients $\vartheta_1$ and $\vartheta_2$. The moderation impact of labor, argued in Hypothesis 2, is tested using coefficients $\vartheta_3$ and $\vartheta_4$. In other words, Hypothesis 2 examines if the linear and curvilinear effects of traffic on sales depend on the level of labor. We avoided other higher-order terms in our linear model because they would likely increase the risk of multicollinearity and would make model interpretation difficult (Aiken and West 1991). We also include the quadratic term of labor because we expect the relationship between store sales performance and store labor to be nonlinear for the following reasons. First, an increase in labor would increase the number of customers served at a decreasing rate, because physical limitations on the number of dressing rooms and checkout counters would result in bottlenecks. Second, according to queueing theory, for a given customer arrival rate, an increase in the number of servers would decrease customers' waiting time in a nonlinear fashion. Specifically, after a certain number of servers, each additional server will have a marginal

**Table 3 Pearson Correlation Coefficients for all Mean-Centered Variables**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. $ASALES_{it} - ASALES_i$ | 1 | | | | | | | |
| 2. $ATRANS_{it} - ATRANS_i$ | 0.877*** | | | | | | | |
| 3. $ATRAF_{it} - ATRAF_i$ | 0.792*** | 0.899*** | | | | | | |
| 4. $ALBR_{it} - ALBR_i$ | 0.460*** | 0.478*** | 0.461*** | | | | | |
| 5. $TRAFVAR_{it} - TRAFVAR_i$ | 0.237*** | 0.292*** | 0.373*** | 0.223*** | | | | |
| 6. $MISMATCH_{it} - MISMATCH_i$ | 0.454*** | 0.553*** | 0.658*** | 0.099*** | 0.206*** | | | |
| 7. $CR_{it} - CR_i$ | −0.078*** | −0.074*** | −0.436*** | −0.105*** | −0.262*** | −0.366*** | | |
| 8. $ABV_{it} - ABV_i$ | 0.466*** | 0.053*** | 0.061*** | 0.107*** | −0.018** | −0.015* | −0.038*** | |
| 9. $ADJI_t - ADJI$ | 0.056*** | 0.030*** | 0.014 | 0.089*** | −0.018** | 0.022** | 0.028*** | 0.079*** |

*Note.* For every pair of variables, the table provides the Pearson's correlation coefficient and its $p$-value for the hypothesis $H_1$: $|\rho| \neq 0$.
*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

impact on reducing customers' waiting time. Finally, prior literature finds a concave relationship between sales and labor (Fisher et al. 2006).

In the second stage, we use the estimated value of the fixed effect, $\hat{\vartheta}_i$, as the dependent variable in the regression against interday traffic variability and store-specific time-invariant control variables represented by the column vector $Z_i$.

$$\hat{\vartheta}_i = \alpha + \gamma_1 Z_i + \gamma_2 TRAFUNC_i + \epsilon_i \tag{1b}$$

Here $\vartheta_0 - \vartheta_7, \alpha, \gamma_2$ denotes scalars, whereas $\vartheta_8$ and $\gamma_1$ denote row vector parameters. We define $\gamma_1 = [\gamma_{1,1}, \gamma_{1,2}, \ldots, \gamma_{1,n}]$ and $\vartheta_8 = [\vartheta_{8,1}, \vartheta_{8,2}, \ldots \vartheta_{8,m}]$ where $n$ and $m$ denote the number of time-invariant and time-variant control variables, respectively.

An important consideration in our choice of the estimation methodology is the issue of potential endogeneity between contemporaneous labor and sales. In general, a regression between sales and labor could result in biased coefficient estimates for labor for the following reasons. First, retailers typically plan labor based on expected demand. For example, retailers may schedule more labor when they expect higher demand because of a promotional event. Thus, if expected demand is not controlled for, the regressions of sales against labor would result in biased coefficient estimates for labor. Second, not controlling for time invariant omitted factors such as store size and manager skills could result in biased estimates. Finally, there is a possibility of reverse causality in regressions using aggregate data of sales and labor, because store managers can observe sales and change labor. In our case we expect the endogeneity bias to be mitigated for the following reasons. We use actual traffic to control for unobserved events such as promotions when retailers would schedule more labor. Next, we use store fixed effects to control for time-invariant factors such as store size that would drive both sales and labor. Finally, because our observations of sales and labor data are at a daily level, our data set does not suffer from reverse causality; i.e., because labor schedules are typically frozen at least a day in advance, managers cannot change labor for the latter part of the day based on sales in the earlier part of that day. In addition, we ran an endogeneity test called a $C$-statistic test (Hayashi 2000), defined as the difference of two Sargen–Hansen statistics, and found that the null hypothesis that labor is exogenous is not rejected ($p = 0.28$).

Because mean centering provides an easy interpretation of our coefficients and can potentially alleviate multicollinearity issues (Aiken and West 1991), we mean center $ALBR_{it}$ and $ATRAF_{it}$ and their interaction terms before estimating Equation (1a). Finally, we specify the following model to test Hypothesis 4B, i.e., the impact of conversion rate on future traffic growth:

$$\begin{aligned}\overline{TRAF\ GROWTH}_{ip} &= \alpha_0 + S_i + \delta_m + \beta \overline{TRAF\ GROWTH}_{i,p-1} \\ &\quad + \gamma \overline{CR}_{i,p-l} + \varepsilon_{ip},\end{aligned} \tag{2}$$

where $S_i$ are store dummies; $\delta_m$ are month dummies; and $\alpha_0$, $\beta$, and $\gamma$ are the parameters to be estimated. Recall that $\overline{TRAF\ GROWTH}_{ip}$ denotes the growth in average traffic for store $i$ in period $p$; $\overline{CR}_{i,p-l}$ denotes the average conversion rate for store $i$ in period $p-l$; and $\varepsilon_{ip}$ denotes the error term for store $i$ in period $p$. We choose $l = 1$ week and $1\ldots5$ months. We test the equation for different values of $l$ to determine if conversion rate is a leading indicator of traffic growth. We estimate Equation (2) using a fixed-effects model because the Hausman specification test rejected the random-effects model ($p < 0.01$).

## 5. Results

Table 5 presents the sales regression results for both stages of the estimation procedure required to test Hypotheses 1–3. Model 1 comprises only control variables; none of the key variables of interest are included. Then we enter the key variables of interest one by one, as shown in Models 2–4 of Table 5. Model 4 is the full model with all the variables. We replace intraday traffic variability with labor-traffic mismatch in Model 5.

Hypothesis 1, that store sales volume is an increasing concave function of traffic, is supported across Models 2–4. In Model 4 we find that the coefficients of $ATRAF_{it}$ and $ATRAF_{it}^2$ are both statistically significant ($p < 0.01$). For values of traffic and labor corresponding to the mean, increasing average traffic per hour by one unit increases average sales volume per hour by \$9.97. For values of labor corresponding to the mean and traffic at a higher level of distribution (corresponding to the mean plus one standard deviation), increasing average traffic per hour by one unit increases average sales volume per hour by \$8.14. For values of labor corresponding to the mean and traffic at a lower level of distribution (corresponding to the mean minus one standard deviation), increasing average traffic per hour by one unit increases average sales volume per hour by \$11.80. Our results posit a benefit to retailers that identify stores for which the marginal impact of traffic on sales is higher and have targeted marketing campaigns for those stores.

Hypothesis 2 predicts that with increasing levels of labor, the impact of store traffic on sales volume will be even more positive. We find that the coefficients of both interaction terms, $\vartheta_3$ and $\vartheta_4$, are significant in Model 4 at $p < 0.01$. For values of store labor

**Table 5 Regression Results for Testing the Effect of Traffic Characteristics and Labor on Store Sales**

| Dependent variable: Average sales per hour ($ASALES_{it}$) | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | | | Longitudinal regression | | |
| $ATRAF_{it}^{c}$ | | 0.009*** | 0.009*** | 0.010*** | 0.010*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| $ATRAF_{it}^{c2}$ | | −0.00002*** | −0.00003*** | −0.00003*** | −0.00003*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| $ALBR_{it}^{c} \times ATRAF_{it}^{c}$ | | | 0.001*** | 0.001*** | 0.001*** |
| | | | (0.000) | (0.000) | (0.000) |
| $ALBR_{it}^{c} \times ATRAF_{it}^{c2}$ | | | −0.000003** | −0.000004*** | −0.000002** |
| | | | (0.000) | (0.000) | (0.000) |
| $TRAFVAR_{it}$ | | | | −0.316*** | |
| | | | | (0.037) | |
| $MISMATCH_{it}$ | | | | | −0.005*** |
| | | | | | (0.001) |
| $ASALES_{i,t-1}$ | 0.130*** | −0.006 | −0.012 | −0.001 | −0.011 |
| | (0.009) | (0.010) | (0.010) | (0.010) | (0.010) |
| $ALBR_{it}^{c}$ | 0.068*** | 0.033*** | 0.037*** | 0.039*** | 0.029*** |
| | (0.006) | (0.004) | (0.004) | (0.004) | (0.004) |
| $ALBR_{it}^{c2}$ | −0.003*** | −0.001 | −0.005*** | −0.005*** | −0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $ADJI_{t}$ | 1.423 | 3.733*** | 3.746*** | 3.935*** | 3.384*** |
| | (1.045) | (1.039) | (1.022) | (1.023) | (1.018) |
| Holiday | 0.055*** | −0.057*** | −0.056*** | −0.045*** | −0.054*** |
| | (0.010) | (0.012) | (0.012) | (0.012) | (0.012) |
| Daily, monthly, and temperature dummies | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.509 | 0.669 | 0.672 | 0.678 | 0.675 |
| Number of observations | 11,130 | 11,130 | 11,130 | 11,110 | 11,110 |
| | | | Cross-sectional regression | | |
| $TRAFUNC_{i}$ | | | | −6.507*** | −6.812*** |
| | | | | (1.349) | (1.388) |
| $APCI_{i}$ | 0.068 | 0.059 | 0.057 | 0.006 | 0.051 |
| | (0.231) | (0.255) | (0.257) | (0.194) | (0.209) |
| $ACOMP_{i}$ | −1.291 | −1.456 | −1.487 | −1.572** | −1.588** |
| | (0.830) | (0.927) | (0.934) | (0.709) | (0.714) |
| Intercept | 0.207 | 0.241 | 0.247 | 1.358*** | 1.396*** |
| | (0.169) | (0.191) | (0.193) | (0.275) | (0.283) |
| $R^2$ | 0.039 | 0.039 | 0.040 | 0.471 | 0.472 |
| Number of observations | 41 | 41 | 41 | 41 | 41 |

*Notes.* The table reports the estimates of the following models: (1) $y_{it} = \vartheta_0 + \vartheta_i + \vartheta_1 X_{it} + \vartheta_2 W_{it} + \xi_{it}$ and (2) $\hat{\vartheta}_i = \alpha + \gamma_1 Z_i + \gamma_2 V_i + \varepsilon_{it}$, where $y_{it}$ is $ASALES_{it}$; $\vartheta_i$ are store fixed effects; $\hat{\vartheta}_i$ are the estimated values of fixed effects from (1); $X_{it}$ and $W_{it}$ are time variant independent variables and controls, respectively; $V_i$ denotes a time-invariant independent variable; and $Z_i$ denotes time-invariant controls. The superscript *c* indicates that the variables are mean-centered before being included in the regression. In Model 1 we only include controls. We add the key variables of interest sequentially in Models 2–4. Model 4 is the full model. In Model 5 we substitute $TRAFVAR_{it}$ with $MISMATCH_{it}$. Robust standard errors clustered at store level are in parentheses. We report the within $R$-squared for the longitudinal regressions.

** and *** denote statistical significance at the 5% and 1% levels, respectively.

corresponding to mean, mean minus one standard deviation, and mean plus one standard deviation, the marginal returns to traffic for the store with mean traffic are \$10.00, \$8.68, and \$11.32, respectively. Based on Equation (1a), we can write the marginal return to traffic as follows: $\vartheta_1 + 2\vartheta_2 ATRAF_{it} + \vartheta_3 ALBR_{it} + 2\vartheta_4 ALBR_{it} \times ATRAF_{it}$. The marginal return to traffic when traffic and labor are at different levels of distribution than the mean are obtained using the following information: the standard deviation of mean-centered traffic and mean-centered labor are 30.56 and 1.32, respectively. The same values for a store with a traffic level corresponding to mean minus one standard deviation are \$11.83, \$10.19, and \$13.47, respectively. Furthermore, we find that store sales volume exhibits diminishing returns to labor. An earlier study by Ingene (1982) used cross-sectional data to show that sales volume per store increases linearly with store labor. Based on this result, Ingene (1982) suggests that the best measure of labor productivity is sales per employee. Our results, derived from panel data, show that the relationship between sales volume and labor is nonlinear and hence appear to caution against using sales per employee as a metric for labor productivity. In contrast, our finding provides support for the premise of Fisher et al. (2006) that store sales volume is a nondecreasing, concave function of store labor.

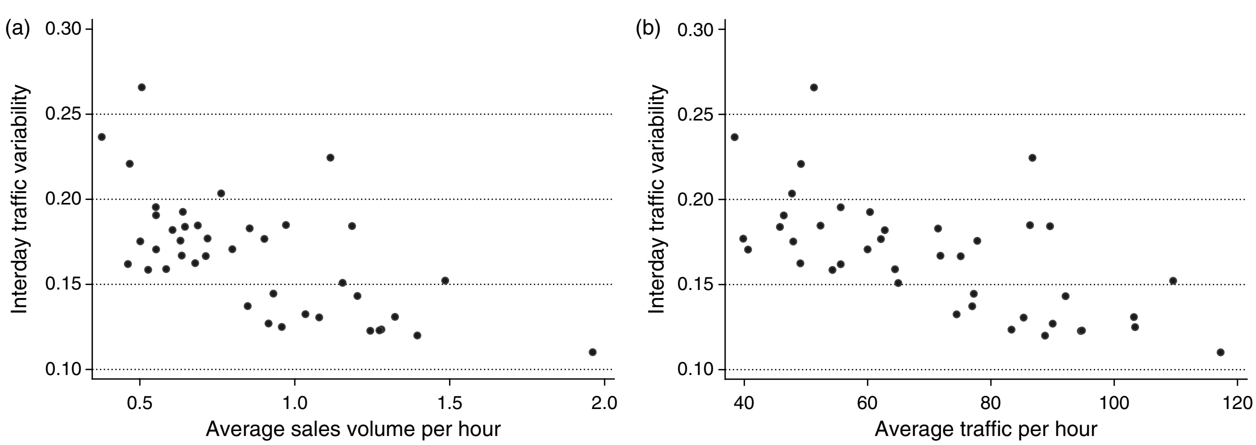
Hypotheses 3A and 3B are also statistically supported ($p < 0.01$), as shown in Model 4. Thus, increases in intraday and interday traffic variability are associated with lower sales per hour in stores. Although our results highlight the need for incorporating traffic variability as an additional factor in labor planning activities, we think that current labor planning practices followed by retailers might exacerbate the impact of traffic variability on store performance for the following reason. As shown in Figures 1(a) and 1(b), stores that have lower sales (or traffic volume) tend to have higher interday traffic variability. As most retailers tend to plan their labor budget as a percentage of sales, these smaller stores could end up having lower labor budgets; lower budgets could prevent such stores from managing the traffic variability by either increasing the "buffer" of labor or by hiring more flexible labor; both are traditional approaches to manage customer arrival variability in service operations (Frei 2006).

In addition to the impact of traffic variability on store sales performance, we tested the effect of labor-traffic mismatch on store sales performance (see Model 5 in Table 5) and found that an increase in labor-traffic mismatch is associated with a significant decrease in sales ($p < 0.001$). Because this variable is constructed using hourly data, this result implies that labor-traffic mismatch across different hours of the day could result in significant deterioration in sales performance of retail stores.

The results of the test of Hypothesis 4A are reported in Model 6 in Table 6. We find that the coefficients of $ATRAF_{it}$ and $ATRAF_{it}^2$ are statistically significant ($p < 0.01$), supporting a decreasing nonlinear relationship between traffic and conversion rate. A decrease in conversion rate will be associated with a decrease in sales, so this result adds to our understanding of why sales exhibit diminishing returns to scale with respect to traffic, as shown in Hypothesis 1. In addition to a linear model specification for conversion rate, we also tested a semilog model, and our results (not reported) support Hypothesis 4A.

Finally, Hypothesis 4B is also supported. The coefficient estimates of average conversion rates on future traffic growth are presented in Table 7. We tested Hypothesis 4B using both definitions of traffic growth shown in §4 and the results are similar. Hence, we present only the result with the first definition of traffic growth (i.e., $\overline{TRAF\ GROWTH}_{ip} \equiv \overline{TRAF}_{ip}/\overline{TRAF}_{i,p-1}$). Columns (1)–(6) of Table 7 report results regarding the short- and medium-term effect of conversion rate on traffic growth. As shown in column (1), increasing the average conversion rate in a given week is associated with an increase in traffic growth in the subsequent week. In columns (2)–(6) we consider monthly lags and find that the relationship between average conversion rate and traffic growth is positive and statistically significant up to five-month lags. Hence, conversion rate is a leading indicator of monthly traffic growth up to five months in advance, even after controlling for lagged traffic growth (i.e., increase in conversion rate in January is associated with increase in traffic growth in June even after controlling for traffic growth in May). These

**Figure 1** **Interday Traffic Variability Decreases with Average Sales Volume (per Hour) and Average Traffic (per Hour)**




*Note.* Average sales volume (per hour) and average traffic (per hour) are not rescaled.

**Table 6** Regression Results for Testing the Effect of Traffic Characteristics and Labor on Conversion Rate, Transactions, and Basket Value

| Dependent variable: | Model 6<br>Conversion rate ($CR_{it}$) | Model 7<br>Average transactions per hour ($ATRANS_{it}$) | Model 8<br>Basket value ($ABV_{it}$) |
|---|---|---|---|
| | Longitudinal regression | | |
| $ATRAF^c_{it}$ | −0.0005*** | 0.009*** | 0.0005*** |
| | (0.000) | (0.000) | (0.000) |
| $ATRAF^{c2}_{it}$ | 0.000002*** | −0.00002*** | −0.00001*** |
| | (0.000) | (0.000) | (0.000) |
| $ALBR^c_{it} \times ATRAF^c_{it}$ | 0.00004*** | 0.001*** | 0.0001 |
| | (0.000) | (0.000) | (0.000) |
| $ALBR^c_{it} \times ATRAF^{c2}_{it}$ | −0.0000003*** | −0.000001 | −0.000001 |
| | (0.000) | (0.000) | (0.000) |
| $TRAFVAR_{it}$ | −0.016*** | −0.180*** | −0.104*** |
| | 0.004 | (0.028) | (0.022) |
| Lagged dependent variable | 0.260*** | 0.002 | 0.098*** |
| | (0.015) | (0.009) | (0.011) |
| $ALBR^c_{it}$ | 0.003*** | 0.026*** | 0.012*** |
| | (0.000) | (0.003) | (0.002) |
| $ALBR^{c2}_{it}$ | −0.0004*** | −0.005*** | −0.0004 |
| | (0.000) | (0.001) | (0.001) |
| $ADJI_t$ | 0.358*** | 1.883** | 2.313** |
| | (0.090) | (0.821) | (0.869) |
| Holiday | 0.005*** | 0.047*** | −0.057*** |
| | (0.001) | (0.009) | (0.006) |
| Daily, monthly, and temperature dummies | Yes | Yes | Yes |
| $R^2$ | 0.330 | 0.836 | 0.116 |
| Number of observations | 11,110 | 11,110 | 11,110 |
| | Cross-sectional regression | | |
| $TRAFUNC_i$ | 0.030 | −5.103*** | −1.627*** |
| | (0.046) | (1.118) | (0.477) |
| $APCI_i$ | 0.034*** | 0.043 | 0.030 |
| | (0.011) | (0.185) | (0.067) |
| $ACOMP_i$ | −0.084** | −1.303* | −0.435 |
| | (0.037) | (0.665) | (0.314) |
| Intercept | −0.003 | 1.059*** | 0.338*** |
| | (0.011) | (0.250) | (0.110) |
| $R^2$ | 0.275 | 0.407 | 0.264 |
| Number of observations | 41 | 41 | 41 |

*Notes.* The table reports the estimates of the following models: (1) $y_{it} = \vartheta_0 + \vartheta_i + \vartheta_1 X_{it} + \vartheta_2 W_{it} + \xi_{it}$ and (2) $\hat{\vartheta}_i = \alpha + \gamma_1 Z_i + \gamma_2 V_i + \varepsilon_{it}$, where $y_{it}$ is $CR_{it}$, $ATRANS_{it}$, and $ABV_{it}$ in Models 6–8, respectively; $\vartheta_i$ are store fixed effects; $\hat{\vartheta}_i$ are the estimated values of fixed effects from (1); $X_{it}$ and $W_{it}$ are time-variant independent variables and controls, respectively; $V_i$ is time-invariant independent variable; and $Z_i$ denotes time-invariant controls. The superscript $c$ indicates that the variables are mean-centered before being included in the regression. Robust standard errors clustered at store level are in parentheses. We report the within $R$-squared for the longitudinal regressions.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

results suggest that increasing average conversion rate has not only a short-term positive impact but also a medium/long-term positive impact on store traffic growth. Although we exercise caution, as our model does not guarantee causality, our results appear to justify the importance placed by retailers on this metric and their efforts to manage it by tying store manager incentives to this metric.

### 5.1. Control Variables

Our analysis also demonstrates that competition is negatively associated with sales volume and conversion rate (Models 4 and 6). We use the number of stores in a mall/shopping center as a proxy for competition and find that stores located in malls/shopping centers with higher competition have lower sales volume and conversion rates. Our measure of competition is noisy and, hence, does not help us rule out an alternate explanation that store sales volume and conversion rates may decrease as the number of window shoppers increases when the number of stores in a mall expands.

In addition, we find that stores located in neighborhoods with higher per capita income have higher conversion rates. The latter could be explained based on the relationship between income and opportunity cost of time (Hurst 2006). As individuals who have higher income are expected to face higher search costs, they may visit a store only when they wish to purchase. We also find positive correlation between the Dow Jones Index and store performance (i.e., sales and conversion rate), which supports the idea that the economy affects consumers' confidence and ability to make purchases. There is anecdotal evidence that store traffic decreases with a decline in economic conditions (Cheng 2009), and our results from Model 6 show that even those shoppers who continue to visit stores may be less inclined to make purchases when the economy declines.

Finally, as expected, we find significant seasonality in store sales volume. Our results show that holidays are associated with higher conversion rates (Model 6) and lower sales volume (Model 4), for a given level of traffic. In other words, a randomly chosen shopper in the store is more likely to make a purchase but is likely to spend less during the holiday season than during the rest of the year. This decrease in basket value during holidays could be driven by price promotions that retailers typically offer during the holiday season (Lam et al. 2001). However, because the traffic during the holiday season is much higher than during other times, an overall increase in sales for retailers occurs.

### 5.2. Impact of Traffic and Labor on Number of Transactions

We repeat our analysis by changing the dependent variable from sales volume to number of transactions.

**Table 7 Regression Results for Testing the Effect of Conversion Rate on Future Traffic Growth (Hypothesis 4B)**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $\overline{CR}_{i,p-l}$ | 1.894*** | 3.360*** | 3.246*** | 2.931*** | 1.170*** | 1.023* |
| | (0.367) | (0.603) | (0.775) | (0.729) | (0.342) | (0.593) |
| $\overline{TRAF\ GROWTH}_{i,p-1}$ | −0.347*** | −0.049 | −0.164*** | −0.084 | −0.008 | −0.080 |
| | (0.024) | (0.077) | (0.054) | (0.055) | (0.060) | (0.073) |
| Intercept | 1.329*** | 1.113*** | 1.255*** | 1.196*** | 1.362*** | 1.464*** |
| | (0.059) | (0.086) | (0.092) | (0.094) | (0.076) | (0.112) |
| Time period dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.201 | 0.600 | 0.633 | 0.653 | 0.733 | 0.724 |
| Number of observations | 2,027 | 410 | 369 | 328 | 287 | 246 |

*Notes*. The table reports the estimates of the following model: $\overline{TRAF\ GROWTH}_{ip} = \alpha_0 + S_i + \delta_m + \beta\overline{TRAF\ GROWTH}_{i,p-1} + \gamma\overline{CR}_{i,p-l} + \varepsilon_{ip}$, where $S_i$ are store dummies and $\delta_m$ are month dummies, and $\overline{TRAF\ GROWTH}_{ip}$ denotes the growth in average traffic for store $i$ in period $p$ and $\overline{CR}_{i,p-l}$ denotes the average conversion rate for store $i$ in period $p-l$. Column (1) shows the effect of the week's $p-1$ average conversion rate on the traffic growth in week $p$ (i.e., $l = 1$ week), controlling for traffic growth in week $p-1$. Columns (2)–(6) show the effect of month's $p-l$ average conversion rate on the traffic growth in month $p$, controlling for traffic growth in month $p-1$ when $l = 1, 2, 3, 4$, and 5 months, respectively. Robust standard errors clustered at store level are in parentheses. Store fixed effects and time effects are not shown in the table.

* and *** denote significance at the 10% and 1% levels, respectively.

We find our results, shown in Model 7 in Table 6, to be qualitatively similar to those obtained from Model 4. Our results show that the number of transactions is increasing with traffic in a concave fashion. We also find that labor moderates the impact of traffic on the number of transactions. Moreover, we find that intraday and interday traffic variability are negatively associated with the number of transactions. Finally, we find that competition, macro-economic conditions, and holidays have significant explanatory power over the number of transactions.

### 5.3. Robustness Checks

We perform several robustness checks (not reported) to determine the sensitivity of our results to model specification and estimation technique employed.

We test the robustness of the results of regression (1a), in which we substituted $ATRAF_{it}$, $ATRAF^2_{it}$, $ALBR_{it} \times ATRAF_{it}$, and $ALBR_{it} \times ATRAF^2_{it}$ with $ATRANS_{it}$, $ATRANS^2_{it}$, $ALBR_{it} \times ATRANS_{it}$, and $ALBR_{it} \times ATRANS^2_{it}$. We do this because in the event that some store managers plan labor based on the purchase incidence rather than on traffic, then transactions would help mitigate the endogeneity bias between sales and labor. We find support of all corresponding hypotheses.

In addition, we checked the robustness of the results of regression (1a) by running multiple regressions for different hours of the day. We did not include intraday traffic variability in those regressions, as this measure was constructed using observations across all hours within a day. We find that our remaining hypotheses are supported.

We performed the endogeneity test and found that the null hypothesis that labor is exogenous is not rejected ($p = 0.28$); we next conservatively assume that the endogeneity bias is present and treat labor as an endogenous variable. We use the sixth and seventh lags of this variable as instruments and estimate the regression using the generalized method of moments technique. We find support for all corresponding hypotheses. In addition, we follow Ton (2009) to add expected sales as an additional control in our analysis to overcome any remaining bias from endogeneity. Because we did not possess data on forecasted sales from this retailer, we estimate expected sales using an AR(7) model of sales after controlling for holidays, months, and days of the week. We find all our hypotheses are supported.

We estimate Model 4 using the Arellano-Bond (1991) estimator for the following reason. Model 4 contains a lagged dependent variable on the right-hand side and is prone to dynamic panel data bias in panels with large $n$ and small $T$ (Nickell 1981). However, in our unbalanced panel data set, where $n = 41$ and the average $T = 271$, we expect the dynamic panel data bias to be negligible (see Judson and Owen 1999 for Monte Carlo simulations of the bias and Roodman 2006). As an additional robustness test, we estimate Model 4 using the Arellano-Bond estimator and find our conclusions unchanged.

We also check the robustness of our results to our measure of interday traffic variability. Recall that we use the residual from an AR(7) model that controlled for months, days of the week, and holidays as a measure of traffic uncertainty faced by stores. We test the robustness of our findings using different lags. For instance, we consider an AR(14) model with additional controls for months, days of the week, and holidays. We also consider models where we include traffic lags of the same day on previous weeks (i.e., lag 7 and lag 14) with additional controls for months, days of the week, and holidays. In all those models, our results on the effect of interday traffic variability are robust to the method by which we measure it.

Finally, we tested the robustness of our findings of Equation (2) to seasonality. Apart from using monthly dummies to control for seasonality, we do the following. We compute the seasonality indices based on a competitor and the overall segment to which this retailer belongs. For the competitor, we obtained the monthly sales reported in 2006–2007 by Ann Taylor Corporation, a competitor of the retail chain in our sample. These data were obtained from PRNewswire. We also obtained the sales of the Women's clothing segment (*North American Industry Classification System*: 44,812) for years 2006–2007 from the census website (http://www.census.gov/retail). We found that our conclusions remain unchanged in both cases. As an additional robustness check we estimated both Equations (1) and (2) after dropping the months of November and December (where we would expect traffic to be higher because of seasonality), and our findings were robust.

One caveat to our robustness checks is that $ALBR_{it} \times ATRAF_{it}^2$ is not always significant. Because the inclusion of higher-order terms in a linear model increases the risk of multicollinearity and makes model interpretation difficult, Aiken and West (1991) suggest adding such terms only if there is a significant increase in explanatory power. We find that the term $ALBR_{it} \times ATRAF_{it}^2$ is associated with a small increase in within $R$-squared. So we tested an alternate model without this term and found that all our hypotheses were supported and this model was robust to all the above tests.

## 6. Discussion

In this section, we explore the impact of traffic on basket value. To do so, we replace conversion rate with basket value as the dependent variable in Model 6 and use the coefficient estimates from the basket value regression (see Model 8) to plot basket value against traffic. We plot three lines corresponding to labor levels at the mean, one standard deviation above the mean, and one standard deviation below the mean. We find that basket value exhibits an inverted-U relationship with traffic. About 19% of our observations lie to the right of the inflection point. In addition to a linear model specification for basket value we also tested a semi-log model and find support that basket value exhibits an inverted-U relationship with traffic.

Our result that basket value initially increases with traffic might be surprising because one may expect that basket value would decrease with traffic as responsiveness within the store declines. However, we note that, because conversion rate is less than 100% in our case, we only observe basket value of customers who decide to purchase. This metric would be similar to basket value in the overall population if the decision to purchase was independent of how much the shoppers were planning to purchase in the first place. But we do not believe this to be the case for the following reason.

In queueing theory, it is common to assume that customers would renege (or balk) if the waiting time exceeds their maximal willingness to wait, i.e., their patience threshold. The maximal amount of time customers are willing to wait would depend on the perceived benefit they would receive from their purchase, because consumer utility is typically assumed to increase with the amount of goods consumed. Therefore, we expect that consumers who are planning to purchase more, i.e., those with larger basket values, would be willing to wait longer. Thus, as traffic increases we expect waiting time to increase as well (for a given level of labor), resulting in greater reneging (and balking) among customers who intended to purchase smaller baskets. Therefore, we expect observed basket values to increase with higher traffic through self-selection. Finally, the decline in basket value for large values of traffic could be driven by stockouts and phantom stockouts in the store. In addition, congested stores may make it harder for store associates to cross-sell and for shoppers to shop around, resulting in lower basket values.

Anecdotal evidence supporting our argument can be found. Many retail stores have priority or express lanes, i.e., special checkout counters for customers buying fewer items, because customers who buy fewer items are expected to be more resentful of waiting long times than those who buy large baskets. We showed this result to several practitioners, and they concurred. One of them commented that examination of abandoned shopping carts in their stores revealed that customers planning to purchase one or two items are more prone to reneging/balking.

Our results help us document how the basket value metric changes with traffic, but we exercise caution when trying to infer the customer behavior from this result because of the self-selection mechanism described above. Thus, we do not claim that customers' purchase behavior follows the basket value metric. Future research may use customer data, which may be available from retailers that have loyalty programs, to examine how customer behavior around basket sizes change with traffic.

## 7. Managerial Implications and Conclusions

The decline in conversion rate with traffic is of enormous importance to retail managers, as it indicates that their investments in driving traffic to their stores would not yield the desired return. Further, our results show that an increase in conversion rate is associated with an increase in future traffic growth. Thus, customers who were disappointed with the customer service level in the store may not only delay their purchase, but they may also decide to switch to competing retailers and create negative publicity for the store through the word-of-mouth effect (Park et al. 2010). Therefore, a decline in conversion rate would not only hurt retailers in the short term but also over the long term from lower traffic growth in the future.

Our results also suggest different strategies to improve store performance. An obvious suggestion, based on the results of Hypothesis 2, would be to increase staffing levels to improve conversion rate. However, retailers are averse to increasing labor expenses in their stores (Ton 2009, Fisher and Raman 2010). Hence, we recommend two other approaches. First, the concave relationship between sales and labor implies that retailers may follow the approach proposed in Fisher et al. (2006), whereby retailers reallocate labor across stores based on the sales lift. That is, retailers should shift labor budget from stores where the marginal impact of labor on sales is low to stores where it is high. Second, our results suggest that incidences of balking and reneging are probably high among customers who intended to buy few items. Retailers need to redesign their store processes to enable quick checkouts for such impatient customers.

Our study is the first in operations management to analyze traffic data in the retail context. Other settings exist within operations management literature in which traffic data have proven to be valuable inputs to improve planning. For example, numerous analytical models and simulation techniques for staffing decisions have been developed over the years in the call center literature (for a survey of this literature, see Gans et al. 2003). Several empirical studies analyzed call data to estimate the parameters of different statistical models used to characterize call arrivals and then use those parameters to forecast call arrivals. As Gans et al. (2003, p. 122) point out, the "modeling and control of call centers must necessarily start with careful data analysis." Our study hopes to provide such an impetus in the context of retailing, where recent technological advances have enabled retailers to collect traffic data directly or through the help of third-party providers such as Kronos Inc., ShopperTrak, SMS, Traf-Sys, and Trax Sales.

Several limitations in our study relate to issues of data availability. One of the drivers of store performance is the product availability in a store. Although all the stores in our study are under the same ownership, creating the expectation that the service level would be similar across stores, fluctuations could exist in the service level across—as well as within—stores that could be driving some of our results on sales performance. Unfortunately, we could not obtain any information on inventory levels for the retailer we studied, and as a result, we could not control for actual inventory. In addition, we did not have any information on product price, which also plays an important role in customer conversion and store sales performance. We also did not possess any information on store manager tenure or employee knowledge, which would affect store sales performance. Finally, besides average daily temperature, other weather-related measures such as precipitation could affect store sales performance. Unfortunately, we could not obtain such data for all stores in our sample.

We expect the qualitative aspects of our results to be generalizable to many other retailers; however there are a few limitations that we wish to point out. We study an apparel retailer where customer service plays an important role. Different retailers, however, could require different levels of customer service to drive sales performance. Therefore, future research might study the moderating impact of labor on sales performance in other retail settings to determine how different factors such as customer expectations and type of merchandise being sold affect this relationship. Also, we do not possess data on the number of children entering the store, store space, gift cards, and returns, which could potentially affect some of our results. Further, some customers may purchase through different channels, that is to say, online, catalog, or in-store from the same retailer. It is unclear how failure to convert in the store would affect eventual purchases from these customers. Such data would be useful to understand the impact of store traffic on sales performance better.

Our paper identifies several opportunities for future research. One valuable area of research is the development of analytical models that would enable better staffing decisions. Our study shows that traffic uncertainty affects store performance. Hence, it is important to analyze the statistical properties of retail traffic patterns and build stochastic models that could facilitate store traffic planning as well as scheduling. Researchers in call center management have built such analytical models to enable better staffing decisions. Labor planning in retail settings has additional complexities that are not found in call center management. For example, call centers have the ability to react quickly to increases in call volume, as they can quickly add resources, who can work from home. In addition, many companies, including inContact, LiveOps, and Stringcan, exist to help call centers adopt the work-at-home agent model by providing solutions for virtual call center technologies and processes. Such a model is clearly not possible in retail, so different planning strategies to handle traffic variability are required. Several studies have shown the impact of marketing activities, such as advertisement, price promotions, etc., on driving store traffic. An unintended consequence of these actions could be increasing traffic variability. Thus, future research may assess the impact of various marketing activities, like "early bird specials" and "blue light specials," on traffic variability and uncertainty and their subsequent impact on store operations.

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