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. We determine that this relationship is driven by a decline in conversion rate with traffic (as opposed to a decline in basket value). Our results show that an increase in conversion rate is associated with an increase in future traffic growth. We also find that increases in intra-day and inter-day traffic variability are associated with a decrease in store sales volume, while an increase in store labor is associated with an increase in sales volume.

Key words: store performance; traffic variability; traffic uncertainty; store labor management; retail operations

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 having desirable properties such as high foot-traffic of their 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 sportspeople, 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 experience a good shopping service that encourages customers 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., Walters and Rinne 1986, Walters and MacKenzie 1988, Lam et al. 2001). However, little empirical evidence exists on the impact of traffic on store performance. Specifically, the relationships between store traffic characteristics—such as mean traffic, intra-day traffic variability, and inter-day 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 effective labor planning and scheduling models and the effective utilization of store labor, which is the second largest expense for retailers, as noted in 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 performance of different stores. Traditional store performance metrics such as sales and profits do not provide the whole picture, as they do not reveal to retailers the sales potential of their stores and 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 traditional[1] retailers because of anecdotal evidence that an increase in conversion rate is positively associated with an increase in customer loyalty.[2] 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. 2007 and Netessine et al. 2010), the conversion rate of retail stores in our study exhibits considerable heterogeneity; it varies between 7% - 25% across stores and time. Consequently, we can study separately the relationship between traffic characteristics and the components of sales, viz. conversion rates and basket value.[3] 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 both intra-day traffic variability and inter-day 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 in our paper. 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. We also find that both intra-day traffic variability and inter-day traffic variability are associated with decreases in store sales volume.

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[1] In e-commerce conversion rate is a widely used metric of performance.

[2] Several studies conducted by Deloitte and Touche have led its analysts to conclude that lost conversion and lost customer loyalty are strongly related (Conroy and Bearse 2006).

[3] Basket value, also known as sales per customer, provides a retailer with the average transaction in dollars. It is also used to measure staff productivity in environments in which sales are mostly driven by sales associates.

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. 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. (2007) that reallocation of payroll budget across stores based on the marginal impact of labor on sales would yield increase in sales.

Third, we find that conversion rate decreases non-linearly 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 longer-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. While 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. 2007, 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 and provides empirical evidence for developing such analytical models.[4]

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

[4] 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. (Patton 2006). In addition, many companies, including inContact, LiveOps, and Stringcan, exist to help call centers adopt the work-at-home agent model by providing solutions on 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.

conversion rate to compensate store associates (Kroll 2009). Our results justify the importance placed by retailers on this metric. However, the non-linear 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 labor is 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 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).

The rest of the paper is organized as follows: in §2 we review relevant literature; in §3 we develop our hypotheses; in §4 we describe our data and the econometric models we use for estimation. In §5 we present our empirical results and some sensitivity analysis. In §6 we discuss the implications of our research on retail managers. Finally, we conclude with a discussion of the limitations of our study and directions for future research in §7.

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 stock-outs (Ton and Raman 2006, Ton and Raman 2010) and were found to impact retail store performance significantly. Fisher et al. (2007) 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, and they propose reallocation of labor across stores to address the execution issues and increase sales. Further proof of the importance of store labor is given 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. Further, Hise et al. (1983) use survey data to show that store managers' experience and the number of employees are significant in explaining sales volume of a retailer. Finally, Ton (2009) shows that an increase in store labor is associated with higher profits through its 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. 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 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, since 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), which assesses the effectiveness of marketing activities on store traffic, transactions, and sales volume. Our paper differs from Lam et al. (2001) in both motivation and methodology. While Lam et al. (2001) use traffic as a dependent variable, 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. In addition to the above paper, an earlier paper by Lam et al. (1998) uses store traffic data to study labor scheduling. This paper uses traffic data from one store to show that the relationship between traffic and sales volume is actually non-linear. 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.

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, US retailers invested about $17.2 billion in advertisements[5]. 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 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 performance. However, the impact of traffic on sales performance is not directly linear due to several reasons. First, for a given level of store labor, we expect an increase in store traffic to lead to a lower number of transactions as a result of a decline in customer service. When traffic increases in a store, sales associates become engaged with some customers, causing other customers who seek help in making purchase decisions to renege or balk. This problem leads to lost sales opportunities and could be exacerbated in stores with large execution issues, such as phantom stock-outs, during which customers may need store associates' help to even locate the product. Furthermore, sales associates are likely to spend less time with individual customers when they are aware of others waiting for their service. This tendency could lead to a decline in customer service with increasing traffic. Finally, an increase in store traffic could also lead to longer queues at checkout counters, resulting in abandonment or balking.

Increase in traffic could also lead to crowding, which has been found to negatively impact the shopping experience. Studies of crowded stores have found customers to 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, Eroglu et al. 2005). 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

[5] http://online.wsj.com/article/SB10001424052748704328104574520040776817068.html

interact with the dissatisfied and/or aggressive[6] customers, having 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. Store associates play a critical role in enhancing customer service. Fisher et al. (2007), 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. Numerous examples of retailers adopting different strategies to improve customer satisfaction with store labor can be found in the business press. For instance, Kovac et al. (2009) state that Best Buy re-trained its store employees so that they could identify and better serve different customer segments. In addition to re-training store associates, the company increased staffing levels during peak shopping hours so that higher-value customers could receive focused assistance. Such staffing practices have helped Best Buy gain higher customer satisfaction ratings and higher sales volume (Kovac et al. 2009). This finding leads 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 inter-day traffic variability and intra-day traffic variability on store sales performance. Increase in inter-day traffic variability could affect sales performance as follows. Increase in inter-day traffic variability would lead to greater difficulty in planning store labor from day-to-day, resulting in greater mismatches between store labor required to manage in-store customers and actual store labor present in the store. When the required store labor exceeds actual store labor, the customer service within the store would decline, resulting in fewer customer purchases.

We then discuss the impact of intra-day traffic variability on store sales. While inter-day traffic variability increases the difficulty in *planning* labor, increase in intra-day traffic variability could cause an increase in difficulties in *scheduling* labor. Labor scheduling is a complex function that requires matching the supply of available store labor with the planned labor (or demand). Store labor usually comprises full-time employees, part-time employees, and temporary workers. These

[6] Overcrowded retail environments induce the same aggressive behaviors as those observed in prisons, dormitories, residential settings, etc. (Lepore 1994).

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 intra-day 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 under-staffing at different hours of the day.

Therefore, we hypothesize the following:

HYPOTHESIS 3a. *The greater the inter-day traffic variability, the lower the store sales performance.*

HYPOTHESIS 3b. *The greater the intra-day traffic variability, the lower the store sales performance.*

Next, we discuss the relationship between traffic and conversion rates. We expect that increase in traffic would lead to lower conversion rates for the reasons mentioned earlier, such as decline in customer service, crowding and its implications on the shopping experience. Therefore, we hypothesize that

HYPOTHESIS 4a. *Increase in store traffic is associated with a decrease in conversion rate.*

Finally, we discuss the relationship between conversion rate and future traffic growth. Conversion rate not only reflects the effectiveness of in-store logistics but also customer satisfaction. In particular, increase in conversion rate can be treated as a signal of increase in 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, increase in conversion rate implies that more customers are purchasing, suggesting an increase in customer satisfaction with the retailer. Increase in customer satisfaction, on the other hand, 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. *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.

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. Retailer Alpha operates over 200 stores in 35 states of the United States, Puerto Rico, the United States Virgin Islands, and Canada as of July 2008. The stores are located primarily in regional shopping centers and in freestanding street locations. The study period was from January 1, 2007 to December 31, 2007.

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 entrance 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; prevent certain types of counting errors;[7] and time-stamp each record, enabling the breakdown of data to any desired time increment.

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 are 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 is not released for customer use until it meets the third party's contractual criteria for accuracy, which is usually in the 96% to 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 used the count as a proxy for competition. Out of 60 stores, 5 stores were located in freestanding street locations, and 5 stores were located in malls that did not have a working website. Moreover, there were 9 stores for

[7] For example, customers would need to enter through fields installed at a certain distance from each entrance of the store in order for their traffic to be included in the counts. This precaution prevents cases in which a shopper enters and immediately exits the store from being included in the actual traffic counts.

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 focus only on those stores for which we could obtain complete information with respect to the above variables. Our final sample had data from 41 stores. 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 United States National Climatic Data Center in Asheville, NC. 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; its 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 5 zip-codes, we use the closest station within 20 miles in these instances.

To control for economic conditions, we collect data on the Dow Jones Industrial Average (DJI) using the Wharton Research Data Services (WRDS). 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 were highly correlated; hence, we only use per capita income in our analysis.

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. Finally, 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: $\overline{TRAF\ GROWTH}_{ip} \equiv \frac{\overline{TRAF}_{ip}}{\overline{TRAF}_{i,p-1}}$. An alternate definition of traffic growth is the following:

$\overline{TRAF\ GROWTH}_{ip} \equiv \frac{\overline{TRAF}_{ip}-\overline{TRAF}_{i,p-1}}{\overline{TRAF}_{i,p-1}}$. We use the alternate definition to test the robustness of our findings. Finally, we calculate basket value in the following way: $BV_{it} = SALES_{it}/TRANS_{it}$.

Independent Variables

We divide traffic per day ($TRAF_{it}$) and labor hours per day (LBR_{it}) with 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 intra-day traffic variability using hourly traffic data as shown below.

$$TRAFVAR_{it} = \sigma_{it}/\mu_{it}$$

Here, $TRAFVAR_{it}$ denotes the coefficient of variation of traffic for store i on day t, σ_{it} and μ_{it} denote the standard deviation and mean of hourly traffic on day t for store i. 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,

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

Next, we define inter-day traffic variability in the following way. First, we note that inter-day 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 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 κ lags and n is the number of observations.

In order to select the lag length κ, we start with a maximum lag of 7 and decrease it gradually to the appropriate lag until the AIC is minimized[8]. 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

[8] There is no general rule with regards to how one can choose a maximum lag length to start with. Some researchers use the following rule of thumb: start with a maximum lag length equal to the cubic root of the number of observations which is $\sqrt[3]{365} \cong 7$ in our case.

(SBIC) and the Hannan-Quinn Information Criterion (HQIC) and the results are consistent. Therefore, we choose an order of 7 in our traffic autoregressive model and obtain the following model:

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

Here, δ_h denotes holiday dummies and δ_m denotes monthly dummies. 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*$_i \equiv$ sd(ε_{it} /*TRAF*$_{it}$), where sd(·) denotes the standard deviation. We estimate the regression coefficients $b_{i0} - b_{i9}$ using Ordinary Least Squares (OLS).

Our approach of measuring inter-day 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 inter-day traffic variability as a proxy for traffic uncertainty. To further test the robustness of our results, we measure inter-day traffic variability using three alternate models. We describe these models in the sensitivity analysis section.

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 retailer 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 (δ_h) that is set to 1 up to 3 days before major holidays, such as the Christmas season (Dec. 23-31), Easter, Memorial Day, Independence Day, Labor Day, Martin Luther King Day, Mother's Day, Veterans Day, and Thanksgiving Day.

Seasonality could also affect store performance. We control for seasonality by introducing monthly dummies. Sales store performance would also be affected by the level of labor at store *i* on day *t*. As prior literature has assumed a concave relationship between labor and sales volume we introduce a linear and a quadratic term of average labor hours per hour (e.g., $ALBR_{it}$, and $ALBR_{it}^2$) to control for labor.

Next, positing that store sales performance would depend on the prevailing national macroeconomic conditions, we use the Dow Jones Industrial Average (DJI) 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 Lam et al.'s (2001) approach 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 in order 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 dataset.

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 $8919, 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. Tables 3 and 4 present the correlations among mean-centered longitudinal and cross-sectional variables, respectively.

Model Specification and Estimation Methodology

Our Hypotheses involve testing both time-variant as well as 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[9] (Fitzmaurice et al. 2004). In Stage 1, 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.

$$ASALES_{it} = \vartheta_0 + \vartheta_i + \vartheta_1 ATRAF_{it} + \vartheta_2 ATRAF_{it}^2 + \vartheta_3 ALBR_{it} * ATRAF_{it} + \vartheta_4 TRAFVAR_{it} + \vartheta_5 W_{it} + \xi_{it} \qquad (1a)$$

Here ϑ_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 due to unobservable manager skills that drive store labor and sales. For example, Siebert and Zubanov (2010) find that able managers could achieve up to 13.9% higher sales per worker. W_{it} is a column vector of control variables that include labor, time dummies to control for time-specific effects, and a lagged dependent variable as it is a good predictor of future sales. In the second stage, we use the estimated value of the fixed effect,

[9] This two-stage method is sometimes called the *NIH Method* because it was popularized by statisticians working at the National Institute of Health (Fitzmaurice et al. 2004). An alternate approach would be to combine $(1a)$ and $(1b)$ into one equation that can be estimated as a random-effects model. However, the Hausman specification test rejected the random-effects model in favor of the fixed-effects model (p<0.01).

$\hat{\vartheta}_i$, as the dependent variable in the regression against inter-day traffic variability and store-specific time-invariant control variables represented by the column vector Z_i.

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

Here $\vartheta_0 - \vartheta_4, \alpha, \gamma_2$ denote scalars, whereas ϑ_5 and γ_1 denote row vector parameters. We define $\gamma_1 = [\gamma_{1,1}, \gamma_{1,2}, \dots, \gamma_{1,n}]$ and $\vartheta_5 = [\vartheta_{5,1}, \vartheta_{5,2}, \dots, \vartheta_{5,m}]$ where n and m denote the number of time-invariant and time-variant control variables, respectively.

One of the important estimation issues that needs to be handled in our analysis is the potential endogeneity between contemporaneous labor and sales. Store labor could be endogenous with sales because retailers typically plan labor based on expected sales. Thus, the use of contemporaneous labor could lead to biased estimates of some of our coefficients. So, we instrument labor, its square, and the interaction term using their respective lags from 1 to 7 i.e., $ALBR_{i,t-k}, ALBR^2_{i,t-k}, ALBR_{i,t-k} * ATRAF_{it}$, where k=1...7. Our approach of using lagged values of labor as instruments is similar to that of Bloom and Van Reenen (2007) and Siebert and Zubanov (2010).

Hypotheses 1 and 2 are tested by using the coefficient estimates ϑ_1, ϑ_2, and ϑ_3. Hypotheses 3a and 3b imply that $\gamma_2 < 0$ and $\vartheta_4 < 0$, respectively. In addition, we replace $ASALES_{it}$ with $ATRANS_{it}$ and CR_{it} to test the impact of traffic and labor on the number of transactions and conversion rate (Hypothesis 4a) respectively.

Finally, we specify the following model to test Hypothesis 4b, i.e., the impact of conversion rate on future traffic growth:

$$\overline{TRAF\ GROWTH}_{ip} = \alpha_0 + S_i + \delta_m + \beta\, \overline{TRAF\ GROWTH}_{i,p-1} + \gamma\, \overline{CR}_{i,p-l} + \varepsilon_{ip} \quad (2)$$

where S_i are store dummies; δ_m are month dummies; $\alpha_0, \beta,$ and γ 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 ε_{ip} denotes the error term for store i in period p. We note that our model is conservative, as we use traffic growth lagged by one period only while average conversion rate is lagged up to l periods. We test the equation for different values of l to determine the predictive power of lagged conversion rate. We estimate equation (2) using a random-effects model.

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 hypothesized variables are included. Then we enter the variables corresponding to each of the Hypothesis one by one as shown in Models 2-5 of Table 5. Model 5 is the full model with all the variables.

Hypothesis 1, that store sales volume is an increasing concave function of traffic, is supported across models 2-5. In Model 5 we find the coefficients of $ATRAF_{it}$ and $ATRAF_{it}^2$ are both statistically significant ($p<0.05$). For values of traffic and labor corresponding to the mean, increasing average traffic per hour on day *t* by 1 unit, increases average sales volume per hour by $9.64, representing an increase of 1.12% in average sales volume per hour. 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 on day *t* by 1 unit, increases average sales volume per hour by $2.90, representing an increase of 0.21% in average sales volume per hour. 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 on day *t* by 1 unit, increases average sales volume per hour by $16.37, representing an increase of 4.42% in average sales volume per hour. We demonstrate concavity using the estimated parameters in the Appendix. Our results posit a benefit to retailers who identify stores for which the marginal impact of traffic on sales is higher and have targeted marketing campaigns for those stores.

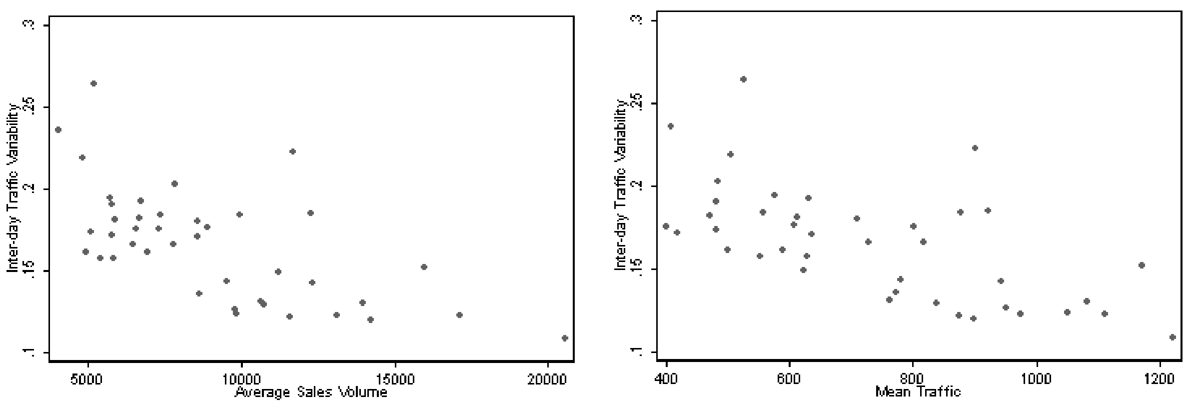
Hypothesis 2 predicts that with increasing levels of labor, the impact of store traffic on sales volume will be even more positive. We find that the coefficient of the interaction term, ϑ_3 is significant in Model 5 at $p<0.01$. For values of store labor corresponding to mean, mean minus one standard deviation, and mean plus one standard deviation, the marginal returns to traffic for the store with mean traffic are $9.64, $1.53, and $17.74 respectively.[10] The same values for a store with a traffic level corresponding to mean minus one standard deviation are $16.37, $8.27, and $24.47, 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 non-linear and, hence, appear to caution against using sales per employee as a metric for labor productivity. On the other hand, our finding provides support for Fisher et al.'s (2007) premise that store sales volume is a non-decreasing, concave function of store labor.

Hypotheses 3a and 3b are also statistically supported ($p<0.05$) as shown in models 4 and 5. Thus, increases in intra-day and inter-day traffic variability are associated with lower sales per hour in stores. While our results highlight the need for incorporating traffic variability as an additional factor in labor planning activities, we are unaware of any retailer who currently does so. In fact, we think

[10] Based on Equation ($1a$), we can write the marginal return to traffic as follows:
$\vartheta_1 + 2\vartheta_2 ATRAF_{it} + \vartheta_3 ALBR_{it}$.

that current labor planning practices might exacerbate the impact of traffic variability on store performance for the following reason. As shown in Figures 1a and 1b, we find that stores that have lower sales (or traffic volume) tend to have higher 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.[11]

Figures 1a and 1b: Inter-day Traffic Variability Decreases with Average Sales Volume and Mean Traffic



The results of the test of Hypothesis 4a is reported in Model 7 in Table 7. We find the coefficients of $ATRAF_{it}$ and $ATRAF_{it}^2$ are statistically significant ($p<0.01$) supporting a decreasing non-linear relationship between traffic and conversion rate. Since decrease in conversion rate will be associated with a decrease in sales, this result adds to our understanding of why sales exhibits diminishing returns to scale with respect to traffic, as shown in Hypothesis 1.

Finally, Hypothesis 4b is also supported. The coefficient estimates of average conversion rates on future traffic growth are presented in Table 6. Note that we tested Hypothesis 4b using both definitions of traffic growth and the results are similar. Hence, we present only the result with the first definition of traffic growth (i.e., $\overline{TRAF\ GROWTH}_{ip} \equiv \frac{\overline{TRAF}_{ip}}{\overline{TRAF}_{i,p-1}}$). Columns (1)-(6) of Table 6 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 four-month lags. Hence, conversion rate is predictive of monthly traffic growth up to 4 months

[11] Employing slack resources and flexible labor practices are "classic" approaches for accommodating customer arrival variability in service operations (Frei 2006).

in advance even after controlling for lagged traffic growth (i.e., conversion rate in January is predictive of future traffic growth in April even after controlling for traffic growth in March). We note that it is possible that conversion rate may also have a longer predictive power and that the loss of significance after 4 months may be driven by the fact that we have fewer observations. These results suggest that increasing average conversion rate has not only short-term positive impact but also a medium/long-term positive impact, on store traffic growth. While 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.

Control Variables

Our analysis also demonstrates that competition is negatively associated with sales volume and conversion rate (Models 5 and 7). 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 sales volume and 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 conversion rate, which supports the idea that the economy affects consumers' confidence and ability to make purchases. While there is anecdotal evidence that store traffic decreases with decline in economic conditions (Cheng 2009), our results from Model 7 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 7). In other words, a randomly chosen shopper in the store is more likely to make a purchase during the holiday season than during the rest of the year.

5.1. 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. The results of the regression with number of transactions as the dependent variable are summarized in Table 7 (Model 6). We find our results to be qualitatively similar to those obtained from Model 5. 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 intra-day traffic variability is negatively associated with the number of transactions. However, we do not find any support that inter-day traffic variability has an effect on the number of transactions. So, we test alternate model specifications and find that inter-day traffic variability is negatively associated with number of transactions[12]. Finally, we find that competition, per capita income, and holidays, have significant explanatory power over the number of transactions.

5.2. Sensitivity Analysis

In this subsection, we perform sensitivity analysis on the fixed-effects full model (Model 5) with sales volume as a dependent variable to test the robustness of our findings. First, we test the robustness of the results of regression $(1a)$ in which we remove the lagged dependent variable (i.e., $ASALES_{i,t-1}$). The results of the estimation of the above model are presented in Table 8 Column (1) and we find support of all Hypotheses (1-3).

Next, we test the robustness of the results of regression $(1a)$ in which we remove covariates one at a time and rerun the model. First, we remove the dummy variable for holidays. Second, we remove the month covariates. Third, we remove the temperature covariates. We find support of all Hypotheses (1-3) under all alternate model specifications. We only report in the paper the results of the estimation of the model with no dummy for holidays (Model s2 in Table 8 Column (2)) since the results are qualitatively the same.

We also check the robustness of our results to our instrument selection. We test different combinations of instruments in our model. For instance, Model s3 is estimated by using instruments that involve only labor of the same day previous week (i.e., $ALBR_{i,t-7}, ALBR_{i,t-7}^2$, $ALBR_{i,t-7} * ATRAF_{it}$). As shown in Table 8 Column (3) our results are robust. In addition, to checking the robustness of our findings to instrument selection, we test an alternate model (s4) shown in Column (4) where contemporaneous labor is replaced with lagged labor, i.e., labor from the previous day ($ALBR_{i,t-1}$). We find support of all our Hypotheses (1-3) under this model specification.

Finally, we check the robustness of our results to our measure of inter-day traffic variability. Recall that we use the residual from an AR(7) model that controlled for months and holidays as a measure of traffic uncertainty faced by stores. We test the robustness of our findings by using different combinations of the control variables in the underlying AR(7) model. For instance, we looked at the following combinations: (1) an AR(7) traffic model that controls for days of week, months, and holidays, (2) an AR(7) model that controls for days of week and months; and (3) an AR(7) model that controls for months only. We find that our results on the effect of inter-day traffic variability (not reported) are robust to the method by which we measure it.

[12] The details of those models are available on request.

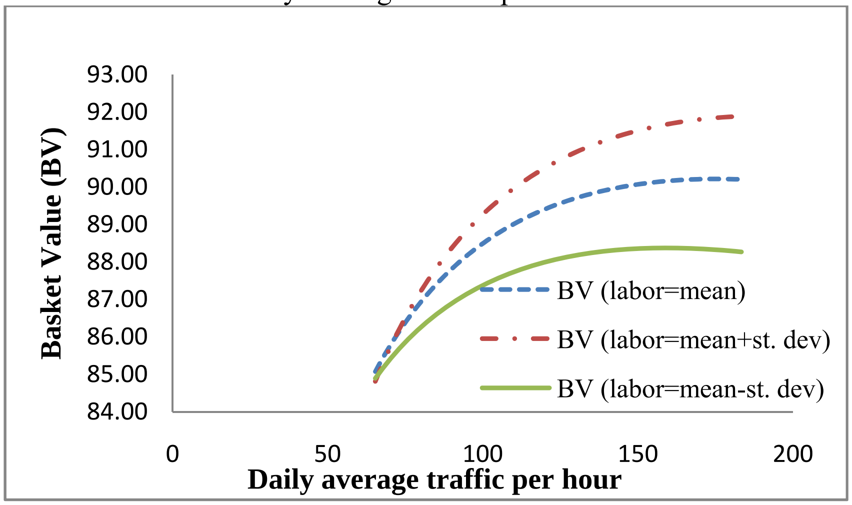
6. Discussion

In this section we synthesize the various results we have reported so far. The main focus of the paper is to study the relationship between traffic and sales performance in retail stores. Results of Model 5 showed an increasing concave relationship between sales volume and traffic. In other words, retail sales volume exhibits diminishing returns to increases in traffic. This relationship could be explained by a decline in conversion rate with an increase in traffic, or a decline in basket value, or both. Results of Model 7 showed that conversion rate decreases with an increase in traffic. Next, we examine how basket value changes with an increase in traffic. To do so, we use the coefficient estimates from Models 5 and 6 to plot basket value against traffic, as shown in Figure 2 for the average store in our chain.[13] 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 increases with traffic in a concave fashion. We test the statistical significance of the relationships by replacing conversion rate with basket value (BV) as the dependent variable in Model 7 and find this relationship to be significant ($p<0.001$) as shown in Table 7 Column (3).

If customers were homogenous, then we expect their basket value to remain unchanged with traffic (holding everything else constant). However, basket value could decrease with traffic if customers decide to purchase less as a consequence of poor customer service or crowding in the stores. Our findings, on the contrary, indicate that basket value increases with daily average traffic per hour non-linearly. While we do not have any evidence to propose a causal explanation for this result, we believe that our results may be driven by shopping habits of high-value customers for this retailer who may visit the stores on high-traffic days such as weekends, when the average traffic per hour would be high. Combining this result with the one from Model 7, (i.e., conversion rate decreases with increase in traffic) our findings imply that this retailer may be potentially losing sales of its high value customers on these days. Furthermore, as results of testing Hypothesis 4b show, decrease in conversion rate is associated with decrease in future traffic growth. Thus, our findings suggest that not only could this retailer be losing the sales of its high value customers during those days when the traffic is high, but it may also be losing customer loyalty in this segment.

[13] The "average store" is a hypothetical store, which is characterized by the mean values of all independent variables except traffic and labor.

Figure 2: Change in Basket Value with Daily Average Traffic per Hour for a Retail Store in our Sample



Finally, our results 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 imply that retailers may follow the approach proposed in Fisher et al. (2007), 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. The second approach is based on the labor practice of Best Buy. Kovac et al. (2009) state that Best Buy is highly successful in training its employees to identify high-value customers who arrive during peak period and cater to them. Both these approaches, along with planning tools that help retailers plan labor to manage traffic variability, should help improve store performance.

7. Conclusions

Our paper characterizes the relationships between store traffic characteristics, labor, and sales performance for a retail chain. In addition, it investigates the relationship between traffic and conversion rates as well as conversion rates and future traffic growth. We show that retail sales performance exhibits diminishing returns to increases in traffic. We also show that labor moderates the impact of traffic on store sales performance. Furthermore, we show that the variability of both intra- and inter-day traffic is negatively associated with store sales volume. Finally, we show that conversion rate declines non-linearly in traffic, and an increase in conversion rate is associated with an increase in future traffic for a store.

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 (see Gans et al. 2003 for a survey of this literature). 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. Recent technological advances have also enabled retailers to collect traffic data, and retailers have shown considerable interest in using traffic data to make staffing decisions.[14] As Gans et al. (2003) 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.

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. While 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 with respect to the 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 posses any information on store manager tenure as well as employee knowledge which affects to a great extent store sales performance. While we control for holidays when apparel retailers offer pricing discounts, it is possible that the retailer offered discounts during other times of the year that affected sales performance.

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 the nature of business affects this relationship.

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. 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. As such, future research may assess the impact of

[14] Many companies, including Kronos Inc., ShopperTrak, SMS, Traf-Sys, and Trax Sales, provide hardware and software solutions to track traffic and help plan labor.

various marketing activities, like *"Early Bird Specials"* and "*Blue Light Specials*"[15] on traffic variability and uncertainty and their subsequent impact on store operations.

Appendix

Proof of Concavity of Sales Volume

We next show the concavity of the sales volume equation (see below) with respect to traffic and labor.

$$\begin{aligned} ASALES_{it} \; &= \vartheta_0 + \vartheta_i + \vartheta_1 ATRAF_{it} + \vartheta_2 ATRAF_{it}^2 + \vartheta_3 ALBR_{it} * ATRAF_{it} + \vartheta_4 TRAFVAR_{it} \\ &\quad + \vartheta_5 W_{it} + \; \xi_{it} \qquad (1a) \end{aligned}$$

We first show the concavity of sales volume in terms of traffic, and then in terms of labor. The second partial derivative of $ASALES_{it}$ with respect to $ATRAF_{it}$ is $2\vartheta_2$ where the coefficient estimate ϑ_2 is presented in Table 5. Note that the coefficient estimate for $ATRAF_{it}^2$ is negative and statistically significant (p<0.01) in Model 5. Hence, the second partial derivative of $ASALES_{it}$ with respect to $ATRAF_{it}$ is $2\vartheta_2 = 2 * (-0.091) < 0.$ Thus, sales volume is a strictly concave function in terms of traffic.

We next show the concavity of sales volume in terms of labor. The second partial derivative of $ASALES_{it}$ with respect to $ALBR_{it}$ is $2\vartheta_{5,2}$ where $\vartheta_{5,2}$ is the coefficient estimate of $ALBR_{it}^2$. The coefficient estimate for $ALBR_{it}^2$ is negative and statistically significant (p<0.01). The second partial derivative of $ASALES_{it}$ with respect to $ALBR_{it}$ in Model 5 is $2\vartheta_{5,2} = 2 * (-41.674) < 0$. Thus, sales volume is a strictly concave function in terms of labor.

[15] "*Blue Light Specials*" is a sales tactic introduced by an Indiana Kmart store manager to increase sales by dropping prices on slow moving merchandise. Kmart used to advertise the days the specials would take place. In those days the customers would flock the store running after the flashing blue light as it moved from one store section to another.

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 inter-day traffic variability for store location *i*
$TRAFVAR_{it}$	Intra-day traffic variability 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

Raw Variables	Variable Name	Mean	Std. Dev.	Min	Max
Longitudinal Variables					
	$TRAF_{it}$	724	365	209	2309
	$TRAFVAR_{it}$	0.642	0.162	0.269	1.066
	CR_{it}	0.139	0.032	0.071	0.252
	BV_{it}	90	22	39	159
	$TRANS_{it}$	97	45	29	280
	$SALES_{it}$	8919	5117	1413	38056
	LBR_{it}	56	19	24	122
	OPER HRS_{it}	11	1	6	14
	$TEMP_{it}$	64	15	18	93
	DJI_{t}	13186	505	12128	14086
Cross-sectional Variables					
	PCI_{i}	36092	19359	12763	92940
	$COMP_{i}$	171	47	95	313
	$TRAFUNC_{i}$	0.165	0.032	0.109	0.264
Transformed Variables					
	$ATRAF_{it}$	70	37	19	226
	CR_{it}	0.139	0.032	0.071	0.252
	BV_{it}	90	22	39	159
	$ATRANS_{it}$	9	4	3	27
	$ASALES_{it}$	860	490	155	3143
	$ALBR_{it}$	5	2	2	19

Table 3: Pearson Correlation Coefficients for all Mean-centered Variables

	1	2	3	4	5	6	7
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. CR_{it}-CR_{i}	-0.078***	-0.074***	-0.436***	-0.105***	-0.262***		
7. BV_{it}-BV_{i}	0.466***	0.053***	0.061***	0.107***	-0.018**	-0.038***	
8. DJI_{t}-DJI	0.056***	0.030***	0.014	0.089***	-0.018**	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: $|\rho|\neq 0$. **, *** denote statistical significance at the 5% and 1% levels, respectively.

Table 4: Correlations among Cross-Sectional Variables

	1	2	3
1. $TRAFUNC_i$	1		
2. PCI_i	0.0103	1	
3. $COMP_i$	0.0135	-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: $|\rho| \neq 0$.

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**	**Note**
First Stage						
$ATRAF_{it}$		12.265***	1.589	2.116**	2.116**	H1
$ATRAF^2_{it}$		-0.01***	-0.085***	-0.091***	-0.091***	H1
$ALBR_{it}$*$ATRAF_{it}$			3.924***	4.052***	4.052***	H2
$TRAFVAR_{it}$				-379.529***	-379.529***	H3(b)
$ASALES_{i,t-1}$	0.279***	-0.031***	-0.053***	-0.040***	-0.040***	Control
$ALBR_{it}$	459.478***	-28.246	215.855***	213.561***	213.561***	Control
$ALBR^2_{it}$	-25.707***	1.14	-42.125***	-41.674***	-41.674***	Control
DJI_t	0.045**	0.017	0.019	0.020	0.020	Control
Temp2	-9.085	28.790*	29.506	27.092	27.092	Control
Temp3	-43.649*	19.985	21.542	18.463	18.463	Control
Temp4	-77.080**	8.984	13.649	10.430	10.430	Control
Holiday	125.745***	-25.806**	-16.277	-6.030	-6.030	Control
Monthly Dummies	Yes	Yes	Yes	Yes	Yes	Controls
R^2	0.5471	0.8016	0.7259	0.7345	0.7345	
Number of observations	6279	6279	6279	6272	6272	
Second Stage						
$TRAFUNC_i$					-1655.428**	H3(a)
PCI_i	-0.001	0.002*	-1.166***	0.002	0.002*	Control
$COMP_i$	0.119	-1.092**	-1.166***	-1.059***	-1.041***	Control
Intercept	-1438.365***	180.591**	-173.188**	-28.864	341.441**	
R^2	0.0471	0.1106	0.1676	0.1357	0.2726	
Number of observations	41	41	41	41	41	

Note: *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. In Model 1 we only include controls. In the next models we include in addition to controls the following variables: (1) $ATRAF_{it}$ and $ATRAF^2_{it}$ in model 2, (2) $ATRAF_{it}$, $ATRAF^2_{it}$, and $ALBR_{it}$*$ATRAF_{it}$ in model 3, (3) $ATRAF_{it}$, $ATRAF^2_{it}$, $ALBR_{it}$*$ATRAF_{it}$, and $TRAFVAR_{it}$ in model 4. Model 5 is the fixed-effects full model. Standard errors are not reported in the table for space considerations.

Table 6: 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*** (0.371)	3.36*** (0.636)	3.246*** (0.822)	2.931*** (0.779)	1.169*** (0.369)	1.023 (0.649)
$\overline{Traffic\ Growth}_{i,p-1}$	-0.347*** (0.024)	-0.049 (0.081)	-0.164*** (0.057)	-0.084 (0.058)	-0.008 (0.065)	-0.079 (0.08)
Intercept	1.339*** (0.055)	1.143*** (0.087)	1.274*** (0.089)	1.195*** (0.093)	1.349*** (0.079)	1.44*** (0.117)

Note: *** denote statistical significance at the 1% level. The numbers below the parameter estimates are the respective standard errors. Store effects and time effects are included in the model but not shown in the table. GLS estimators are used. 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 traffic on the traffic growth in month *p*, controlling for traffic growth in month *p*-1when *l*=1,2,3,4, and 5 months, respectively.

Table 7: Regression Results for Testing the Effect of Traffic Characteristics and Labor on Transactions, CR, and BV

	Model 6	**Model 7**	**Model 8**	**Note**
Dependent Variable	**Average Transactions per hour($ATRANS_{it}$)**	**Conversion Rate (CR_{it})**	**Basket Value(BV_{it})**	
First Stage				
$ATRAF_{it}$	0.063***	-0.001***	-0.015	H1/H4
$ATRAF^2_{it}$	-0.001***	-0.000002***	-0.002***	H1/H4
$ALBR_{it}$*$ATRAF_{it}$	0.026***	0.0002***	0.087***	H2
$TRAFVAR_{it}$	-2.821***	-0.024***	-9.430***	H3(b)
Lagged Dependent Variable	-0.011	0.216***	0.063***	Control
$ALBR_{it}$	1.471***	0.015***	5.991**	Control
$ALBR^2_{it}$	-0.264***	-0.002***	-1.110***	Control
DJI_t	0.0001	0.000004**	0.001	Control
Temp2	0.118	0.001	0.890	Control
Temp3	0.183	0.001	-0.768	Control
Temp4	0.217	0.002	-2.089	Control
Holiday	0.448***	0.005***	-4.300***	Control
Monthly Dummies	Yes	Yes	Yes	Controls
R^2	0.8614	0.5448	0.3287	
Number of observations	6272	6272	6272	
Second Stage				
$TRAFUNC_i$	-3.890	-0.102***	-97.815	H3(a)
PCI_i	0.00002***	0.0000003***	0.00004	Control
$COMP_i$	-0.007**	-0.0001***	-0.043	Control
Intercept	0.621	0.125***	88.858***	
R^2	0.2458	0.3453	0.1201	
Number of observations	41	41	41	

Note: *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Models 6-8 correspond to fixed-effects full model for $ATRANS_{it}$, CR_{it}, and BV_{it} respectively. Standard errors are not reported in the table for space considerations.

Table 8: Sensitivity Analysis

Dependent Variable: Average sales per hour (ASALES$_{it}$)	**Model s1**	**Model s2**	**Model s3**	**Model s4**	**Note**
First Stage					
$ATRAF_{it}$	3.072***	2.050**	7.716***	10.107***	H1
$ATRAF^2_{it}$	-0.078***	-0.091***	-0.047***	-0.020***	H1
$ALBR_{it}$*$ATRAF_{it}$	3.504***	4.066***	1.799***	0.567***	H2
$TRAFVAR_{it}$	-378.657***	-381.337***	-286.781***	-219.930***	H3(b)
$ASALES_{i,t-1}$		-0.040***	-0.001	-0.049***	Control
$ALBR_{it}$	228.258***	215.114***	131.913**	-20.833***	Control
$ALBR^2_{it}$	-39.885***	-41.869***	-21.879***	-1.225**	Control
DJI_t	0.021	0.021	0.037***	0.024**	Control
Temp2	23.771	27.131	16.761	17.002*	Control
Temp3	13.532	18.273	31.217**	27.937***	Control
Temp4	5.559	10.160	16.347	13.381	Control
Holiday	-7.357		-54.000***	-45.313***	Control
Monthly Dummies	Yes	Yes	Yes	Yes	Controls
R^2	0.7446	0.7339	0.7874	N/A	
Number of observations	6272	6272	9772	11110	
Second Stage					
$TRAFUNC_i$	-1611.296**	-1654.021**	-1889.900**	-2399.940***	H3(a)
PCI_i	0.002*	0.002*	0.002*	0.002*	Control
$COMP_i$	-0.960**	-1.041***	-0.964**	-1.052**	Control
Intercept	210.439	326.005*	114.561	787.136***	
R^2	0.2583	0.2722	0.2917	0.3222	
Number of observations	41	41	41	41	

Note: *, **, *** denote statistical significance at the 10%, 5%, 1% levels, respectively. Models s1-s4 are different models tested for sensitivity analysis. Model s1 is the basic model with no lagged dependent variable. Model s2 is the basic model with no dummy variable for holiday. Model s3 is the basic model estimated with instruments that involve only labor of the previous week, Model s4 is an alternate model where we have replaced the contemporaneous labor with lagged labor and use no instruments. The first stage of Model s4 has been estimated using feasible generalized least squares and hence R^2 is not reported. Standard errors are not reported in the table for space considerations.

References

Athanassopoulos, A., S. Gounaris, V. Stathakopoulos. 2001. Behavioural responses to customer satisfaction: An empirical study. *Eur. J. Marketing* **35(**5/6**)** 687-707.

Bloom, N., J. Van Reenen. 2007. Measuring and explaining management practices across firms and countries. *Quart. J. Econom*. **122**(4) 1351-1408.

Cheng, A. 2009. Another downturn seen at the mall for the holidays. *Wall Street Journal,* October 20.

Conroy, P., S. Bearse. 2006. Customer Conversion. http://www.deloitte.com/assets/Dcom-UnitedStates/Local%20Assets/Documents/us_cb_conversion_103006.pdf

Dion, D. 1999. A theoretical and empirical study of retail crowding. *European Advances in Consumer Research* **4** 51-57.

DeHoratius, N., A. Raman. 2008. Inventory record inaccuracy: An empirical analysis. *Management Sci.* **54**(4) 627-641.

Eroglu, S.A., K.A. Machleit. 1990. An empirical study of retail crowding: Antecedents and consequences. *J. Retailing* **66**(2) 201-221.

Eroglu, S.A., K.A. Machleit, T. F. Barr. 2005. Perceived retail crowding and shopping satisfaction: The role of shopping values. *J. Business Research* **58**(8) 1146-1153.

Fisher, M.L., 1997. What is the right supply chain for your product? *Harvard Bus. Rev.* **75**(2) 105-116.

Fisher, M.L., J. Krishnan, S. Netessine. 2007. Retail store execution: An empirical study. Working paper, University of Pennsylvania, Philadelphia, PA.

Fisher, M.L., A. Raman. 2010. *The New Science of Retailing.* Harvard Business School Press, Boston, MA.

Fitzmaurice, G.M., N.M. Laird, J.H. Ware. 2004. *Applied Longitudinal Analysis*. Wiley, Hoboken, NJ.

Frei, F. X. 2006. Customer-Introduced Variability in Service Operations. Harvard Business School Note 606-063.

Gans, N., G. Koole, A. Mandelbaum. 2003. Telephone call centers: Tutorial, review, and research prospects. *Manufacturing Service Oper. Management* **5**(2) 79-141

Gómez, M.I., E.W. McLaughlin, D.R. Wittink. 2004. Customer satisfaction and retail sales performance: An empirical investigation. *J. Retailing* **80**(4) 265-278.

Harrell, G.D., M.D. Hutt, J.C. Anderson. 1980. Path analysis of buyer behavior under conditions of crowding. *J. Marketing Res.* **17**(1) 45-51.

Hise, R. T., J. P. Kelly, M. Gable, J. B. McDonald. 1983. Factors affecting the performance of individual chain store units: An empirical analysis. *J. Retailing,* 59(2), 22-39.

Hurst, E. 2006. The Price of Time. http://www.chicagobooth.edu/capideas/sep06/1.aspx.

Ingene, C.A., 1982. Labor Productivity in Retailing. *J. Marketing* **46**(4) 75-90.

Kovac, M., J. Chernoff, J. Denneen, P. Mukharji. 2009. Balancing customer service and satisfaction. http://blogs.hbr.org/hmu/2009/03/strike-a-balance-between-custo.html

Kroll, K.M. 2009. Eye on Productivity. *Stores*, November 2009.

Lam, S.Y., M. Vandenbosch, M. Pearce. 1998. Retail sales force scheduling based on store traffic forecasting. *J. Retailing* **74**(1) 61-88.

Lam, S.Y., M. Vandenbosch, J. Hulland, M. Pearce. 2001. Evaluating promotions in shopping environments: Decomposing sales response into attraction, conversion, and spending effects. *Marketing Sci.* **20**(2) 194–215.

Langer, E.J., S. Saegert. 1977. Crowding and cognitive control. *J. Personality and Social Psychology* **35**(3) 175-182.

Lepore, S. J. 1994. Crowding: Effects on health and behavior. *Encyclopedia of Human Behavior* **2** 43-51.

Netessine, S., M.L. Fisher, J. Krishnan. 2010. Labor planning, execution, and retail store performance: An exploratory investigation. Working paper, University of Pennsylvania, Philadelphia, PA.

Patton, C., 2006. Home Work. http://www.hreonline.com/HRE/story.jsp?storyId=5176412

Raman, A., N. DeHoratius, Z. Ton. 2001. Execution: The missing link in retail operations. *California Management Rev.* **43**(3) 136-152.

Ranaweera, C., J. Prabhu. 2003. On the relative importance of customer satisfaction and trust as determinants of customer retention and positive word of mouth. *J. Targeting, Measurement and Analysis for Marketing* **12**(1) 82-90.

Rumyantsev, S., S. Netessine. 2007. What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing Service Oper. Management* **9**(4) 409-429.

Siebert, W.S., N. Zubanov. 2010. Management economics in a large retail company. *Management Sci.* **56**(8) 1398-1414.

Sulek, J. M., M. R. Lind, A.S. Marucheck. 1995. The impact of customer service intervention and facility design on firm performance. *Management Sci.* **41**(11) 1763-1773.

Ton, Z. 2009. The effect of labor on profitability: The role of quality. Working paper, Harvard University, Boston, MA.

Ton, Z., R.S. Huckman. 2008. Managing the impact of employee turnover on performance: The role of process conformance. *Organization Sci.* **19**(1) 56–68.

Ton, Z., A. Raman. 2006. Cross-sectional analysis of phantom products at retail stores. Working paper, Harvard University, Boston, MA.

Ton, Z., A. Raman. 2010. The effect of product variety and inventory levels on retail store sales: A longitudinal study. *Production Oper. Management* **19**(5) 546-560.

van Donselaar, K.H., V. Gaur, T. van Woensel, R.A.C.M. Broekmeulen, J.C. Fransoo. 2010. Ordering behavior in retail stores and implications for automated replenishment. *Management Sci.* **56**(5) 766-784.

Walters, R. G., S. B. MacKenzie.1988. A structural equations analysis of the impact of price promotions on store performance. *J. Marketing Res.* **25**(1) 51-63.

Walters, R. G., H. J. Rinne. 1986. An empirical investigation into the impact of price promotions on retail store performance. *J. Retailing* **62** (3) 237-266.