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Managing Revenue Across Retail Channels: The Interplay of Service Performance and Direct Marketing

Increased internal pressure to make marketing accountable, combined with market pressure from the proliferation of new service delivery channels, requires retailers to better understand the differential impacts of marketing efforts across channels now more than ever. In this article, the authors (1) develop and test a theoretically grounded framework for the interplay of objective service performance and direct marketing in shaping retail revenue over time through two distinct service delivery channels (on-site and remote) and (2) conceptualize service delivery channel–specific servicescapes as facilitative mechanisms for the effectiveness of objective service performance and direct marketing. The authors test the conceptual framework with multisource data from a major national pizza retailer comprising a field study based on a time series of 223 weeks across five stores of objective marketing and performance data (delivery time) and a cross-sectional survey of the retailer's customers. They find that objective service performance and direct marketing interact by exhibiting a trade-off effect contingent on specific aspects of the servicescape. When both objective service performance and direct marketing levels are high, servicescape quality design perceptions alleviate the trade-off effect in on-site delivery channels, and servicescape time/effort cost perceptions do so in remote delivery channels. The authors conclude with a discussion of implications for research and practice.

Keywords: service performance, direct marketing, service delivery channel

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Managing retail revenue expansion over time through marketing strategies is a fundamental challenge for modern retail organizations and a long-standing problem of interest in marketing (Bolton, Lemon, and Bramlett 2006; Bolton, Lemon, and Verhoef 2008; Rust et al. 2004; Rust and Chung 2006). Sales (i.e., revenue growth) are foundational components of stock, market, and accounting firm valuation and a common performance measure for public and private organizations. To increase sales, successful retail organizations depend on the effective translation of objective service performance goals into achievable operational process initiatives. For example, McDonald's relies on its drive-through service times as an indicator of objective service performance, with the explicit goal of serving all customers within 90 seconds (Marla King, McDonald's International, cited in Hess, Ganesan, and Klein 2003).

Although theory has noted that service performance plays a key role in driving sales revenue in retail organizations, retailers also rely heavily on direct marketing to propel revenue growth. In 2012, retailers spent $10.7 billion on direct marketing, which represents 43% of U.S. retailers' total advertising spending (Laughlin 2013), making it their most dominant marketing communication method. Research has shown that retailers can benefit by investing even more in direct marketing (Büttner and Göritz 2008) and by better understanding how "elements of a coordinated marketing strategy influence the purchase behavior of different segments over time and how ... this affect(s) the firm's revenue stream" (Rust et al. 2004, p. 78). Importantly, the same authors question whether investments in marketing communications campaigns or service performance have a greater influence on financial outcomes.

In this article, we respond to this call for research by conceptualizing and empirically testing a dynamic model of the contingent impact of objective service performance, direct marketing, and servicescape dimensions on retail revenue over time across two distinct service delivery channels (on-site and remote). We make the following contributions to the literature. First, we conceptualize and empirically isolate the interplay of objective service performance and direct marketing in shaping retail revenue over time. Specifically, drawing from usage dominance theory

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(Deighton, Henderson, and Neslin 1994), we develop a model to examine the contingent effects of objective service performance and direct marketing in generating retail revenue over time. Theoretically, general interactive models for marketing communications have been suggested in advertising research (e.g., Smith and Swinyard 1982; Vakratsas and Ambler 1999); however, none of them (1) focus conceptually on the interplay of objective service performance and direct marketing or (2) have been empirically tested. In general, the literature streams on service and marketing communications have evolved independently. Had retail giant J.C. Penney better understood the implications of such interactions, it might not have faced massive same-store sales losses (approximately 20%) resulting from its January 2012 decisions to simultaneously cancel direct mail promotions and eliminate sales commissions (Tuttle 2012). In addition to our model's contribution to research, it is managerially actionable because it provides direction for managing the interactive impact of objective service performance and direct marketing on retail revenue.

Second, we theorize the differential impact of marketing efforts across two unique service delivery channels characterized by varying degrees of service separation (on-site and remote service delivery). Drawing from environmental psychology (Donovan et al. 1994) and customer experience (Baker et al. 2002) research, we conceptualize service delivery channel–specific servicescapes as components that shape the effectiveness of objective service performance and direct marketing. Retailers are increasingly expanding their use of diverse service delivery channels to connect with consumers. For example, Redbox, the movie rental kiosk giant, recently introduced instant online streaming options to provide current and new customers a new channel through which to rent and purchase movies remotely on any capable device. Wal-Mart, Sears, REI, and many other retailers offer customers the option of ordering online with home delivery or of picking up purchases at a preferred location (site-to-store shipping). Evidence has suggested that the introduction of new service delivery channels can financially benefit the firm (Geyskens, Gielens, and Dekimpe 2002), and yet little is known about the role of the service delivery channel and associated servicescape in shaping the impact of marketing efforts on revenue. Rust and Chung (2006) investigate which mechanisms facilitate the translation of marketing communications and objective service performance into sales revenue in different channels. We identify service delivery channel–specific servicescapes as facilitative mechanisms that shape the impact of objective service performance and direct marketing on retail revenue and, in so doing, fill this gap in the literature.

Finally, we address the noticeable dearth of empirical research in retailing that links objective service performance with objective financial outcomes over time (for a review, see Table 1). This can be problematic for retail managers who need more responsive metrics on which to base daily decisions without incurring the high cost of constantly monitoring consumer perceptions. Regarding the lack of empirical evidence directly linking service quality and profitability, Zeithaml and Parasuraman (2004, pp. 24–25) argue that "service quality benefits are rarely experienced in the short term and instead accumulate over time, making them less amenable to traditional research approaches" and state that because many other variables influence short-term financial outcomes, "it can be difficult to isolate the individual contribution of service." This discussion is consistent with calls to address the paucity of research on actionable forward-looking metrics of objective service performance that would enable managers to make informed decisions in a timely (sometimes minute-by-minute) manner (Zeithaml et al. 2006). Our research addresses this issue by using an objective, managerially actionable measure of service performance to assess its impact on retail sales revenue.

We test the proposed conceptual framework with multisource data from a major national pizza retailer that includes a field study based on a time series of 223 weeks across five stores of objective marketing and service performance data (specifically, delivery time) and a cross-sectional survey of the retailer's customers. This article provides several insights for research and practice. First, we find that although objective service performance and direct marketing exhibit a negative interaction over time, servicescape perceptions mitigate this trade-off effect on retail sales. Second, in the remote service delivery channel, we demonstrate that the interplay of objective service performance and direct marketing is contingent on servicescape time/effort cost perceptions. When servicescape time/effort cost perceptions are high, direct marketing exhibits a stronger positive effect on retail sales as objective service performance increases. In contrast, when servicescape time/effort cost perceptions are low, direct marketing has a weaker positive impact on retail revenue as objective service performance increases. Third, in the on-site service delivery channel, we show that when servicescape quality design perceptions are high, objective service performance yields a greater positive effect on retail sales as direct marketing is intensified. In contrast, when servicescape quality design perceptions are low, the impact of objective service performance declines when direct marketing increases from low to high. We proceed by presenting the conceptual framework (Figure 1) and develop hypotheses for the contingent effects of objective service performance and direct marketing in remote and on-site service delivery channels.

Research Background and Hypotheses

Objective Service Performance

Despite its rich conceptualization of service quality, the service quality literature (Parasuraman, Zeithaml, and Berry 1988; Zeithaml and Parasuraman 2004) has indicated that managers "typically do not have daily or even weekly access to customer attitudinal measures to guide them in their everyday performance," and therefore, more actionable components of forward-looking metrics are necessary (Zeithaml et al. 2006, p. 179). This statement is supported by retail practice, in which firms maintain objective service performance indicators and operational service goals, many of which are time based. For example, "time to service the

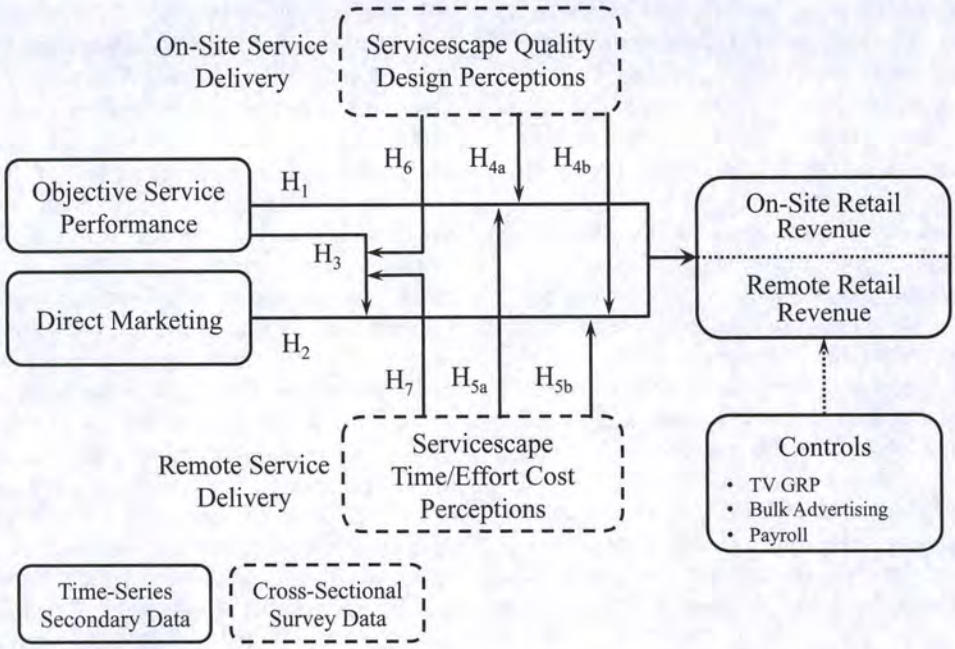
TABLE 1
Review of Objective and Subjective Service Performance Research

Article	Research Description	Research Context	Methodology	Independent Variable		Dependent Variable	
				Objective	Subjective	Objective	Subjective
Cronin and Taylor 1992	Service quality → satisfaction → behavioral intentions	Consumers of firms in one of four industries (n = 660)	Cross-sectional		Service quality (SERVQUAL)		Customer satisfaction, behavioral intentions
Nelson et al. 1992	Hospital service quality leads to financial performance	Consumers from 51 hospitals (n = 15,095)	Cross-sectional		Medical/billing quality, nursing/daily care, admissions, discharges	Earnings per bed, revenue per bed, return on assets	
Boulding et al. 1993	Model of service quality and repurchase intentions as a function of expectations	Experiment (n = 96) and survey (n = 177) in the consumer context	Longitudinal experiment and cross-sectional survey	Experimental manipulation of service performance attributes	Service quality (SERVQUAL) in the survey		Repeat purchase intentions
Rust, Zahorik, and Keiningham 1995	Return on service quality	Customers of a national hotel chain (n = 7,882)	Cross-sectional		Perceptions of service quality attributes		Repeat purchase intentions (market share and net present value derived from them)
Zeithaml, Berry, and Parasuraman 1996	Service quality leads to behavioral intentions	Customers of four firms (n = 3,069)	Cross-sectional		Service quality (SERVQUAL)		Behavioral intentions
Anderson, Fornell, and Rust 1997	Investigates trade-off between customer satisfaction and firm productivity	Consumers (~200 customers of each firm to create index)	Cross-sectional, time-series		Customer satisfaction (Swedish Customer Satisfaction Baromter)	Return on investment and labor productivity	
Bolton 1998	How satisfaction (based on expectations and experiences) affects customer retention	Consumers (n = 650) of a cell phone company	Cross-sectional, time-series		Customer satisfaction, perceived losses, perceived gains	Duration of customer relationship	
Bolton and Lemon 1999	Payment equity perceptions lead to satisfaction, which determines future usage	Consumers of cell phone (n = 409) and television (n = 184) service providers	Longitudinal		Customer satisfaction	Average number of minutes per month usage	

TABLE 1
Continued

Article	Research Description	Research Context	Methodology	Independent Variable		Dependent Variable	
				Objective	Subjective	Objective	Subjective
Bolton, Kannan, and Bramlett 2000	Investigates the conditions in which a loyalty program will have a positive effect on customer evaluations, behavior, and repeat purchase	European consumers (n = 405) of a worldwide financial services provider	Cross-sectional, time-series	Number of prior transactions (control variable)	Repurchase intentions, customer satisfaction	Indicator of customer retention, number of transactions during study period	
Kamakura et al. 2002	Service profit chain inputs → perceptions → intentions → behaviors (and profit)	Brazilian bank customers (n = 3,489)	Cross-sectional	Number of employees, number of ATMs	Perceptions of personnel, perceptions of equipment	Customer behaviors, bank share, number of transactions, relationship duration	Intention to recommend
Anderson, Fornell, and Mazvancheryl 2004	Customer satisfaction leads to customer behavior and, ultimately, future cash flows	Consumers (at least 200 per firm)	Cross-sectional, time-series		Customer satisfaction (American Customer Satisfaction Index)	Shareholder value (Tobin's Q)	
Ngobo 2005	Service quality and satisfaction lead to migration decisions to stay, upgrade, or downgrade	Theater consumers (n = 200)	Cross-sectional and longitudinal survey	Pricing policy, sociodemographics	Service quality, customer satisfaction		Intentions to subscribe, intentions to downgrade
Bolton, Lemon, and Bramlett 2006	Effect of supplier's marketing and service operations on business customers' contract renewal	Business-to-business (2,442 firms that purchase from 143 suppliers)	Longitudinal	Experience quality, design quality, extreme outcomes (measured objectively)		Contract renewal	
Bolton, Lemon, and Verhoef 2008	Firm's decision to upgrade service contracts on the basis of order resolution time, satisfaction, criticality, and price	Renewed contracts (n = 2,076) from 120 firm-customers of a computing support service provider	Longitudinal	Service quality (order resolution time)	Satisfaction, criticality	Customer decision to upgrade	
Agarwal, Malhotra, and Bolton 2010	Cross-cultural versus cross-national differences in the importance of service quality	Banking customers from India (n = 314) and the United States (n = 455)	Cross-sectional		Service quality (SERVQUAL)		Attitude toward the bank, customer satisfaction, patronage intentions

FIGURE 1
Conceptual Framework



customer" and "customer wait time" are common objective measures in retail service industries. Airlines track "on-time flight percentages," and UPS and FedEx use real-time delivery tracking. Retail food providers commonly track a time-based indicator as an objective service performance metric (e.g., drive-through times, queue wait times in restaurants).

Indeed, "service time" is emerging as the frontier of competitive advantage in current retailing practice. In a recent discussion of Amazon's move toward same-day and Sunday delivery, Vicki Cantrell (Senior Vice President and Executive Director, Shop.org, National Retail Federation) stated that retailers' primary means of differentiation is becoming increasingly convenience based because "our number-one commodity as consumers these days is time" (Rhem 2013). Consistent with the view that service operations are important determinants of customer perceptions and behavior (Grönroos 1984; Lehtinen and Lehtinen 1991), we define "objective service performance" as the observable unbiased outcome of the firm's service operation processes and initiatives. Given the stated need in the literature (see Zeithaml et al. 2006), the present objective to assess the dynamic effectiveness of marketing strategies, and retailers' practical emphasis on achieving a competitive advantage, we focus on service delivery time as an indicator of objective service performance.

To conceptualize the impact of objective service performance, we build on the return on quality and the service profit chain literature streams. The return on quality framework suggests that operational investments in service processes can be accounted for by assessing the financial impact of service performance improvements through additional revenues or market value that is created (Rust and Zahorik 1993; Rust, Zahorik, and Keiningham 1995). For example, Kamakura et al. (2002) include operational service indicators (number of employees and automated teller machines [ATMs]) as predictors of bank share, number of transactions, and relationship duration among banking consumers. In a business-to-business context, Bolton, Lemon, and Bramlett (2006) and Bolton, Lemon, and Verhoef (2008) examine the impact of objective measures of service performance from the company's service operations data (service resolution time) on contract renewal and the customer's decision to upgrade. Arguments presented in the service profit chain literature stream (Heskett et al. 1994; Kamakura et al. 2002) have also positioned service performance as an important determinant of a firm's financial outcomes. For example, Heskett et al. (1994) indicate that superior customer service leads to increased financial performance in a consumer service setting. Furthermore, Bolton and Lemon (1999) suggest that future purchase decisions are largely dependent on the actual service experience. These two research streams position objective service performance as a precursor to financial outcomes; however, objective time-based measures of service performance have not been examined in a retail setting. Therefore, we hypothesize the following:

H_1: Objective service performance positively affects retail revenue across service delivery channels.

Direct Marketing Intensity

Retailers use direct marketing as one marketing communication tool in their overall communication portfolio (which may also include television, radio, and print) to reach existing customers. The effectiveness of these vehicles in market building versus revenue expansion differs (Dertouzos and Garber 2006; Montgomery and Silk 1972). Whereas broad

messages delivered to the public (e.g., television, radio) are typically used to capture market share and expand the existing customer base, direct marketing communications are often used to increase revenue from current customers through frequency, quantity, or brand appeals. Accordingly, in predicting new service adoption, Prins and Verhoef (2007) specify two types of marketing communications: direct marketing, which focuses on existing customers, and mass marketing communications, which are used to reach both new and existing customers.

Because the focus of this research is the interface between objective service performance and marketing communications, we examine the influence of direct marketing delivered to *existing* customers (i.e., customers who have already experienced the retailer's objective service performance). We follow prior research (De Wulf, Odekerken-Schröder, and Iacobucci 2001; Iyer, Soberman, and Villas-Boas 2005) and current trends in the industry by focusing on direct marketing intensity. In accordance with Prins and Verhoef (2007) and Schweidel and Knox (2013), we define direct marketing intensity as the volume of customer-tailored messages sent directly to existing customers in efforts to improve brand perceptions and/or increase purchase frequency or quantity.

Customer-tailored messages targeted to specific segments of customers improve the effectiveness of direct marketing for retailers (Iyer, Soberman, and Villas-Boas 2005). For example, Risselada, Verhoef, and Bijmolt (2014) find that direct marketing positively affects consumer adoption of high-technology products. Retailer direct marketing typically includes coupons or promotions bundled together with an advertising message. Importantly, although marketing communications may get lost in the noise of multiple competitive messages, especially in mature and established industries such as retail, recent research has found that simply exposing consumers to customer-tailored direct marketing can have a greater impact on retail revenue than the actual redemption of the offers contained within. In tracking the response to customized coupon mailers from grocery stores, Venkatesan and Farris (2012) find that a sales increase from customers who were merely exposed to customer-tailored direct marketing actually had a greater impact on the overall sales push from direct marketing than offer redemption. This finding helps explain why retailers increasingly rely on direct marketing campaigns to specific segments or individual consumers and are shifting away from mass advertising (Kesmodel 2008; Steel 2008). Although evidence has shown that direct marketing is an effective driver of retail revenue, this is the first research, to our knowledge, that examines the impact of direct marketing across service delivery channels. Thus, we hypothesize the following:

H_2: Direct marketing intensity positively affects retail revenue across service delivery channels.

Interaction of Objective Service Performance and Direct Marketing

Retailers rely on several tools to compete effectively, including pricing, broadly targeted or direct marketing communications, service performance, and the retail environment. The performance impact of any element of the marketing mix depends on other marketing efforts to which the customer is exposed (Shankar 2008; Smith, Gopalakrishna, and Chatterjee 2006). Direct marketing may not always increase retail sales because, for example, consumers may have limited budgets. Thus, intensifying marketing efforts to existing customers by increasing a single marketing investment will likely reach a point of diminishing returns (Freimer and Horsky 2012; Simon and Arndt 1980). Research has also shown that marketing investments may exhibit trade-off effects, especially in retail industries with large investments in one particular marketing vehicle (Venkatesan and Kumar 2004). For example, Prins and Verhoef (2007) find a negative interaction between direct marketing communications and service advertising when investigating the length of time until a customer adopts a new service. As an explanation, they argue that the combination of direct marketing and advertising may create some "kind of overkill" effect (Prins and Verhoef 2007, p. 180). Naik, Raman, and Winer (2005, p. 31) find a negative interaction between advertising and promotional spending for detergent brands: one "interpretation ... is that advertising lowers consumer sensitivity to promotion activities." Thus, in industries such as retail that rely heavily on one particular marketing element, it should be expected that the response to that one element will reach a point of diminishing returns.

We draw from the usage dominance framework (Deighton, Henderson, and Neslin 1994) grounded in the accessibility–diagnosticity theory of information use (Alba, Hutchinson, and Lynch 1991; Lynch 2006) to develop hypotheses regarding these interactive effects. According to accessibility–diagnosticity theory, when consumers are faced with a purchase decision, their choice will be determined by the most accessible and diagnostic information available. This translates into a decreased effectiveness of the less diagnostic information compared with when only one source of information is available. In purchase decisions, consumers may have access to multiple information sources, including direct marketing, advertising, word of mouth, and existing perceptions of the purchase experience. The usage dominance framework (Deighton, Henderson, and Neslin 1994) and accessibility–diagnosticity theory (Alba, Hutchinson, and Lynch 1991; Lynch 2006) argue that when attribute information (e.g., a direct marketing offer) and prior evaluations (e.g., based on prior experience with service performance) are available, prior evaluations are likely to be more diagnostic and accessible. As one source of attribute information becomes more dominant, other sources of information are necessarily less effective. Over time, consumer experiences strengthen their beliefs about the retailer and thus largely guide future purchase behavior, resulting in other sources of information (e.g., direct marketing) becoming less impactful.

This perspective is also advanced by advertising effectiveness models (Smith and Swinyard 1982, Vakratsas and Ambler 1999), which assert that strongly held beliefs are more likely to be produced by experience than through

advertising and that experience-based attitudes exhibit a stronger attitude–behavior link than those built from external information (Fazio and Zanna 1978). A consumer's prior experience is likely to contain a greater depth of information than direct marketing messages and is likely to be more impactful, especially in mature retail industries (Vakratsas and Ambler 1999). Thus, when a retailer offers exceptional service (e.g., Hilton, Amazon.com, Nordstrom), perceptions based on prior experiences are a dominant driver of consumer purchase decisions and are likely to result in an increased share of wallet for the retailer *without* the need to invest heavily in marketing communications. In this situation, the usage dominance effect will result in direct marketing being less effective as objective service performance improves. In contrast, if a retailer offers merely adequate service, having done little to differentiate itself from its competition, direct marketing's effectiveness may be more pronounced because consumers have ambivalent perceptions of prior experiences. In this situation, direct marketing serves to heighten awareness, and in the absence of strong negative or positive service experiences that may overpower the communication, consumers are more likely to respond to the direct marketing. In other words, we expect to observe a trade-off effect of objective service performance and direct marketing over time such that in the presence of both marketing investments, the dominance of one implies a reduced effectiveness of the other; thus, the interaction between the two will be negative. In support of this prediction, Deighton, Henderson, and Neslin (1994) hypothesize and find a negative interaction between prior experience and future advertising in mature, frequently purchased consumer products. Drawing on the usage dominance perspective and related empirical evidence, we expect the following:

H_3: Objective service performance negatively moderates the impact of direct marketing intensity on retail revenue.

Service Delivery Channels and Servicescapes

Consumers react differently to service delivery on the basis of the extent of separation between the customer and service production process (Keh and Pang 2010). Importantly, the amount of separation can vary substantially depending on the service delivery channel. The term "service delivery channel" refers to the specific service delivery mode(s) offered by the retailer (Keh and Pang 2010; Verhoef et al. 2009) and can include several options. For example, health care providers offer phone and online consultations as alternatives to traditional office visits. Banks have mobile apps in addition to online and conventional face-to-face service delivery channels. FedEx offers online scheduling along with the more traditional option of visiting a brick-and-mortar store. Motivated by the perspective that service separation will influence the way consumers respond to objective service performance and direct marketing, we focus on two distinct channels—namely, on-site and remote service delivery channels (Bitner 1992).

Drawing from environmental psychology (Donovan et al. 1994; Russell and Mehrabian 1976) and theoretical frameworks based on the service profit chain (Bolton, Lemon, and Verhoef 2004; Verhoef et al. 2009), we reason that the service delivery channel in which objective service performance and direct marketing are executed is important. Bolton, Lemon, and Verhoef (2004) argue that factors related to the service delivery environment (e.g., hedonic nature of the service, customer involvement) moderate the effectiveness of more concrete marketing instruments (e.g., objective service performance, direct marketing). Scholars have also advanced this view in customer experience research, which has suggested that physical attributes of the service interface and retail environment affect how customers perceive the service experience (Verhoef et al. 2009).

The servicescape, defined as the physical surroundings of the service delivery environment (Bitner 1992), is the lens through which customers perceive and react to the service delivery process (Baker et al. 2002; Verhoef et al. 2009). Although physical aspects of the service delivery environment can be changed, the high cost of doing so makes them a long-term investment rather than a dynamic marketing tool. Recent research has shown that remodeling the servicescape does result in a sales increase (Brüggen, Foubert, and Gremler 2011) and that this effect is greater for new than for existing customers (Dagger and Danaher 2014). Over time, the servicescape becomes part of consumers' mental representation of the retailer, and these fundamental mental representations inevitably shape customer experiences (e.g., service delivery time) and exposure to other marketing investments (e.g., direct marketing).

For example, in 2012 the retail giant J.C. Penney initiated a multidimensional marketing strategy to increase revenue and thwart its decreasing market share. First, it implemented a new employee culture, discouraging aggressive selling through the elimination of sales commissions and training its staff to become product specialists. Second, with the aim of capitalizing on the usage dominance effect of the improved customer service, it introduced "Fair and Square" pricing, offering value through simplified everyday low pricing, and completely eliminated ongoing direct marketing campaigns. These changes prefaced a four-year plan to overhaul the store layout and provide a servicescape that enhanced the shopping experience. Unfortunately, to date, customer response has not met expectations. J.C. Penney customers likely refer to a mental representation based on the traditional servicescape because the new store reconfigurations are yet to be fully implemented. Thus, it is likely that the critical aspects of J.C. Penney's service environment accessed by customers do not complement the firm's new marketing strategy. Exactly which aspects of the servicescape are most critical to the customer depends on the service delivery channel used (Bitner 1992).

We define "on-site service delivery channels" as service delivery channels in which there is no separation in space between the production and delivery of the service to the buyer. On-site service delivery includes going into a store to ship a package with FedEx, talking to a teller inside a bank lobby, and visiting a doctor in her office. Drawing from Bitner's (1990) servicescape framework, we reason that service separation can be characterized by distinct dimensions

of the servicescape. In recent practice, retail establishments such as McDonald's (Gogoi, Arndt, and Moiduddin 2006) and Wendy's (Fletcher 2012) have undergone store reimaging campaigns to enhance consumer perceptions of their servicescapes. These programs called for substantial investments in aesthetic design changes at the service delivery interface ($300,000–$400,000 per store for McDonald's), creating a more appealing experience for the consumer. Anecdotal evidence has suggested that these improvements can drive retail revenue. For example, Wendy's claims that "the unit sales increases of (10 reimaged locations) continue to exceed expectations" (Young 2011). However, there is a notable lack of empirical evidence specifying the link between the servicescape and financial performance outcomes (for an exception, see Brüggen, Foubert, and Gremler 2011).

Conceptual frameworks in service marketing propose that the appeal of the service delivery interface has both affective and cognitive consequences. Bitner (1992) notes that perceptions of servicescapes and associated affect drive consumers' feelings toward the organization and its actions (e.g., direct marketing). We reason that the particular aspects of the servicescape that will be most impactful depend on consumers' motivation for choosing that service delivery channel and differ substantially between on-site and remote service delivery channels (Bitner 1990). Consistent with the servicescape framework, the critical aspect of the servicescape for on-site service delivery channels is the configuration of the physical design of the service delivery environment. Drawing from Baker et al. (2002), we define "servicescape quality design perceptions" as consumer perceptions of the configuration of the physical design (e.g., attractive signage and facilities, appealing color scheme, welcoming lobby, pleasant atmosphere) of the service delivery environment. When a consumer chooses an on-site service delivery channel, the physical design configuration is particularly important because these design elements must accommodate the needs of both customers and employees and provide cues as to the retailer's ability and desire to meet customers' needs (Bitner 1990, 1992).

In other words, servicescape quality design perceptions act as a lens through which consumers interpret the service delivery (Baker et al. 2002), shaping their overall beliefs about the retailer (Verhoef et al. 2009) and subsequently influencing their response to marketing efforts. Although it would be naive to suggest that a well-designed servicescape would make up for poor service delivery or inadequate direct marketing, we believe that servicescapes facilitate the functional role of the marketing mix and provide cues to the consumer as to the firm's ability and intent to provide a satisfactory service experience. In on-site service channels, servicescape quality design perceptions provide such cues and thus influence the effectiveness of other marketing-mix variables. When a customer perceives better servicescape design, the impact of objective service performance and direct marketing will be enhanced. Specifically, we hypothesize the following:

H_4: In on-site service delivery channels, servicescape quality design perceptions enhance the impact of (a) objective service performance and (b) direct marketing intensity on retail revenue.

We define "remote service delivery channels" as service delivery channels in which there is separation in space between the service production and delivery to the buyer. Examples include remote consultations with health care providers conducted online or over the phone; remote pickup of packages by FedEx; online banking; and restaurants that deliver to a customer's residence, hotel, or place of work. Remote service delivery interactions typically offer increased levels of convenience for the customer because they may not have to worry about restrictive business hours, nor do they need to travel to a specific physical location. Thus, consumers who choose a remote service delivery are likely motivated more by convenience than by personal attention (Bitner 1992). For example, if a consumer is more concerned with efficiency than with personal attention, he will choose an ATM rather than entering a bank and interacting with a teller.

Baker et al. (2002) investigate "time/effort cost perceptions," defined as the consumers' perceptions of the time and effort they are likely to expend shopping in a particular channel, and find that these perceptions negatively affect behavioral intentions. In the context of remote service delivery, in which the design of the physical environment is not immediately evident and the primary motivations seem to be efficiency related, consumer perceptions of expended time and effort will be more relevant. Whereas in the on-site delivery channel, we expect quality design perceptions to enhance the effectiveness of other marketing investments, in the remote context, we posit that time/effort cost perceptions will provide the cues through which consumers interpret the service delivery, which subsequently affect other marketing efforts. As we argued previously, fit between consumer goals for using a particular service delivery channel and key aspects of the service interface are likely to increase the effectiveness of contemporaneous marketing efforts (Bitner 1992). In line with consumers' efficiency focus when using remote service channels, operational efficiency should be the primary goal because the consumer never interacts with the firm's physical setting (Bitner 1992). Therefore, we hypothesize the following:

H_5: In remote service delivery channels, lower servicescape time/effort cost perceptions enhance the impact of (a) objective service performance and (b) direct marketing intensity on retail revenue.

In H_4 and H_5, we argue that that physical attributes of the service interface and retail environment affect how customers perceive the service (Verhoef et al. 2009) and therefore enhance the functional effects of concrete marketing instruments (e.g., objective service performance, direct marketing). Specifically, when consumers perceive the service environment as supporting their goals for using a particular service delivery channel, the servicescape should enhance the effectiveness of other marketing strategies. Thus, when a retailer provides high levels of service and strong signals through marketing communications, the perception of a facilitative service delivery environment will enhance the overall consumer response. Although it is

unlikely that any one aspect of the servicescape can overcome negative signals (e.g., poor service, inadequate communications), Bitner (1992) argues that perceptions of the servicescape act as the lens through which other aspects of the service delivery experience are interpreted. This suggests that J.C. Penney (in our previous example) would have benefited by introducing its improved store layout to customers (quality design perceptions) before eliminating direct marketing. In other words, the department store is unlikely to benefit from improvements in service performance until there is alignment throughout the entire service delivery experience (perceptions of the store layout and consistent direct marketing).

Servicescape perceptions play a facilitative or enhancing role rather than a compensating role in influencing marketing instruments. When both direct marketing and objective service performance are average (as expected) or above average, in accordance with servicescape theory (Bitner 1990), servicescape perceptions are likely to further enhance and facilitate their functional impact, thus enhancing their accessibility and diagnosticity and suppressing the expected trade-off effect over time (per H_3 and the usage-dominance argument). In contrast, in the presence of below-average levels of objective service performance or direct marketing, servicescape perceptions are unlikely to compensate for inadequate service or marketing incentives to purchase. As servicescape theory has implied, servicescapes cannot make up for deficient marketing effort, whether in service or marketing communications. However, they can boost the response to marketing efforts by, for example, mitigating trade-off effects of functional marketing instruments. Therefore, we expect that servicescapes that are perceived to be aligned with customer goals (quality design perceptions in the on-site channel and time/effort cost perceptions in the remote channel) will enhance consumers' overall response to other marketing efforts and suppress the trade-off effects hypothesized between objective service performance and direct marketing. Specifically, we hypothesize the following:

H_6: In on-site service delivery channels, servicescape quality design perceptions mitigate the negative interaction of objective service performance and direct marketing intensity on retail revenue.

H_7: In remote service delivery channels, lower servicescape time/effort cost perceptions mitigate the negative interaction of objective service performance and direct marketing intensity on retail revenue.

Method

Research Setting

We selected the pizza restaurant industry as the setting for this research for several reasons. First, it is a highly competitive retail industry in which heavy investments in objective service performance and direct marketing are prevalent. Second, the use of distinct service delivery channels, on-site (in-store carry-out) and remote (home delivery), is an established management practice in this industry. Third, this setting enables remote and on-site service delivery to be matched to the same revenue-generating unit, thus controlling for the effect of unit-specific factors such as management resources and marketing capability. Fourth, although conducting the study across industries could potentially enhance generalizability, it also poses internal validity threats due to uncontrollable and/or unobservable dynamic differences based on industry-specific factors such as competition, as well as irregularity in direct marketing and objective service performance standards and measurement.

On-site service delivery typically involves the customer directly interacting with customer service representatives (CSRs) during both the ordering and service delivery processes. There is often a wait for the customer in the strategically designed customer service lobby, which is in close proximity to the production area. On-site customers are able to experience the entire service production process, beginning with ordering from visually enhanced store menus, witnessing the handmade pizza production, interacting with friendly frontline employees, and eventually smelling their pizza cooking. In contrast, remote service delivery typically involves either contact with a CSR over the phone or no contact at all, if ordering online. Remote customers receive their order from a polite but hurried delivery person, whose primary concern is delivering orders as quickly as possible. Thus, remote customers are not exposed to the carefully designed service environment and must rely on telephone contact for any concerns about their order (before or after delivery).

Data Source and Sampling

To ensure a consistent competitive base for all stores in the study and to minimize the impact of asymmetric competition (Carpenter et al. 1988), we sampled five locations of the same major national pizza franchise located in the Midwest, with geographic delivery boundaries that are contiguous and together entail service coverage to one city. Within each store's delivery area, customers can choose from this franchise or any other national pizza franchise, in addition to numerous local options. Each store sends direct marketing to existing customers within its delivery boundaries, and delivery orders are geographically assigned to each store. Repeat business accounts for more than 90% of retail sales at each of the locations. Consumers can choose between on-site and remote service delivery channels. Pricing and direct marketing content sent to consumers are uniform across the two channels and across stores. Finally, although on-site customers can theoretically choose any store, the delivery boundaries are determined such that the obvious convenience-based choice for on-site pizza orders is the same store from which a given customer would order for delivery.

The final data used in this research originated from three sources. We drew objective service performance and revenues from weekly unit-specific financial reports and compiled direct marketing and other marketing communications data from system-wide archival monthly marketing plans. We collected consumer perceptions of the servicescape, along with other control variables, using a cross-sectional survey delivered to retail customers at the point of

purchase. Drawing from Tellis and Franses (2006), we identified the optimal data interval or the "unit-exposure" time for the field study to be one week, because customers receive a maximum of one targeted direct marketing communication per week but often receive more than one per month. The final database of secondary data (objective service performance, marketing investments, and revenue) contained 1,115 time–store unit observations based on 223 weeks (September 23, 2002–December 31, 2006) of data from five stores. Table W1 in the Web Appendix provides descriptive statistics for the archival data.

Customer service representatives delivered surveys directly to customers at the completion of on-site and remote service delivery experiences so that the amount of time was minimized between service delivery and survey completion and so that consumers would respond to the survey regarding the service delivery channel from which their participation was requested. Five CSRs from each store (2 on-site, 2 remote, and 1 manager, for a total of 20 CSRs and 5 managers) were trained to deliver the packets to customers using a standardized script. In total, each store received 400 surveys (200 on-site and 200 remote) to be delivered. After seven days, the researcher collected any undelivered surveys. To reduce respondent selection bias, and to the extent that operational efficiency was not compromised, every on-site customer who entered the store was asked to participate. Similarly, the remote CSRs solicited participation from every customer to whom they delivered until they exhausted their 100 surveys or until the seven days ended. Survey packets included the survey, a cover letter from the franchisee, a coupon for $5 off their next order, a cover letter from the researchers briefly explaining the research, the incentive for participation (entry into a drawing for one of ten gift cards ranging from $50 to $100 in value), and a postage-paid return envelope addressed to the researchers so that completed surveys were never handled directly by any employees of the restaurant. Because of the sampling method used, it was not possible to send out reminders or second requests to improve the response rates for the surveys. Even so, the overall response rate was 16.64% (290 of 1,743 delivered). Table W2 in the Web Appendix shows response rate information for each store in the sample.

Measurement and Operationalization

We measured direct marketing intensity by the weekly dollar investment in targeted direct mailers[1] (e.g., full-color postcards, menus), which were sent to existing customers (Schweidel and Knox 2013). The specific artwork of the direct mail pieces changed over the study period (although it was always consistent across stores), but the message was aligned with the contemporaneous national advertising campaign along with two or three consistent promotional offers. In other words, the content of the promotional offers was stable across stores and over time. We chose the intensity of targeted direct marketing over other forms of marketing communications because of its prominence in retailers' marketing mix (Levy and Weitz 2007; Zeithaml, Bitner, and Gremler 2009) and because of the focal interest in the interaction between the response to marketing communications and objective service performance (which can only be measured *after* a customer has experienced the service).

A concern with using direct marketing as an explanatory variable for retail revenue is that the promotions or coupons included in direct marketing could drive down the average purchase size as customers redeem the offer and, thus, negatively affect revenue. In our data, this was not a problem. Comparing survey responses with archival direct marketing records showed that the average purchase for customers who had received direct mail in the prior 30 days (μ_{DM} = $17.78) was not significantly different than for those who had not (μ_{noDM} = $16.55; $F(1, 249) = 1.09, p = .30$). Other advertising and marketing communications may also influence existing customers; however, their impact would also extend to new customers who have no previous experience with the retailer. Therefore, the most appropriate communication variable to test our interaction hypothesis is direct marketing delivered to existing customers. To account for the effects of all other marketing communication, we include weekly measures of television (in gross rating points [GRPs]) and bulk advertising (money spent on, e.g., newspapers, local magazines, coupon door-hangers) as controls in the analysis. To incorporate carryover effects of direct marketing (Assmus, Farley, and Lehmann 1984), we created a stock variable (discussed in detail in the "Method of Analysis" section).

In the pizza restaurant industry, service delivery time is the primary objective service performance indicator. Service delivery time is measured objectively and continuously for every order across all stores in the nation, and management relies on it as the operational indicator of objective service performance. Service delivery times are also the primary indicator used to convey performance to upper-level management at any point during daily operations. Managers must meet monthly service delivery time expectations to gain corporate recognition awards and are financially penalized if those expectations are not maintained throughout the month. Delivery drivers call out the service delivery times for every order as they leave the store, and managers must report the daily average service delivery time every night as they call in deposits to the home office. Interviews with managers suggest that other measures of service performance (e.g., number of service failures, telephone CSR service quality, frontline employee interactions, product quality) are also considered; however, in this industry, none of them are heavily relied on, given primary importance, or continuously measured on a daily basis. Thus, the weekly average service delivery time from each store, in minutes, was the target measure of objective service performance. For on-site customers, the service delivery time was captured as the average elapsed time from the moment customers ordered pizza until their order was out of the oven and ready to take home. In the remote channel, the service delivery time is the average elapsed time from the moment customers placed orders until delivery drivers delivered them to the customers' remote location.

[1]Within the context of our data, our measure of direct marketing would be equivalent to a measure based on the number of direct mailers sent out because the costs are charged on a per-mailer fixed rate. This rate stayed constant throughout our entire data set.

Because the average service delivery time implies poorer service as the times increase, we reverse-coded these values. The process used to reverse-code our measures of objective service performance was to divide 1/(actual value) such that the worst weekly objective service performance times (largest actual values) have the smallest values in our analysis. This process allows for a straightforward interpretation of the objective service performance coefficients; a positive sign means that better objective service performance enhances retail revenue.

Zeithaml et al. (2006) provide further support for the current measure by arguing that forward-looking metrics may necessarily be broken down into more actionable components so that managers are able to make informed decisions in a timely (sometimes minute-by-minute) manner. Bolton, Lemon, and Verhoef (2008) use order resolution time and report that it is the primary concern of customers and a key indicator of objective service performance. We also examined consumer perceptions of order accuracy and service quality based on the SERVQUAL scale (Parasuraman, Berry, and Zeithaml 1991). Analyses of variance show that there are no differences between the five retail locations in terms of consumer perceptions of either order accuracy ($F(4, 282) = .403$, $p = .81$), which ranged from 94% to 98% accuracy, or consumer perceptions of service quality ($p > .10$).

Consistent with prior research (Oliva and Sterman 2001), to capture the effect of objective service performance on sales revenue, we incorporated a time lag between the service experience and sales in the analysis. To model this carryover effect, we created a stock variable (Narayanan, Manchanda, and Chintagunta 2005) for objective service performance, which we discuss in the "Method of Analysis" section.

Multi-item scales measuring servicescape time/effort cost perceptions were adapted from Baker et al. (2002) and were consistent with Zeithaml's (1988) conceptualization of the consumers' perceptions of the cost of service. Servicescape quality design perceptions were measured in line with Bitner's (1990, 1992) conceptualization of servicescapes and adapted from Baker et al. (2002). The five items capturing time/effort cost perceptions focused on time/effort cost reduction, and therefore, higher scores represent lower time/effort cost perceptions. Respondents were asked to rate their level of agreement with five items each for design perceptions and time/effort cost perceptions when thinking about the pizza restaurant from which they ordered. We measured all items on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree") and included a "don't know" option in case a remote customer had no experience with the on-site servicescape (see Table 2). In the final analysis, we included the factor-weighted sum of the servicescape perception measures as indices rather than as time-varying factors on the basis of the following considerations. Interviews with the franchisee confirmed that there were no changes to the servicescapes' physical aspects during the period of study, suggesting that servicescape quality design perceptions would be stable. Furthermore, it is unlikely that time/effort cost perceptions would vary over time given that in four of the five stores, the management did not change during our study. (In the fifth store, a manager left the system, and her husband, who had been her assistant manager, was promoted to store manager.)

TABLE 2
Estimated Coefficients from CFA[a]

Items	Factor Loadings[b]	t-Value	Construct Reliability[c]	Variance Extracted[d]	M (SD)	Largest Shared Variance
Servicescape Time/Effort Cost Perceptions			.94	.77	23.12 (6.50)	.74
Thinking about the appearance of the X store you order from, please rate your agreement with the following descriptions...						
•Convenient location	.738					
•Easy to order	.762	12.40				
•Free of clutter	.942	12.94				
•Short wait time	.772	13.06				
•Extremely clean	.914	11.56				
Servicescape Quality Design Perceptions			.94	.77	22.59 (6.56)	.74
Thinking about the appearance of the X store you order from, please rate your agreement with the following descriptions...						
•Attractive signage	.794					
•Nice color scheme	.818	17.60				
•Welcoming lobby	.896	21.42				
•Attractive facilities	.864	22.76				
•Pleasant atmosphere	.953	21.90				

[a]Includes a common method factor that is excluded for clarity.
[b]Standardized coefficients (all $ps < .01$) after controlling for common method, with corresponding t-values in the adjacent column from maximum likelihood solution using AMOS.
[c]Composite reliability per Fornell and Larcker (1981).
[d]Variance extracted by the latent construct from its hypothesized indicators per Fornell and Larcker (1981).

Method of Analysis

In this section, we discuss the psychometric properties of our multi-item measures (Stage I). We follow this with a detailed explanation of the empirical process used in the econometric analysis (Stages II and III).

Stage I: Measurement Model Analysis

We used standard confirmatory factor analysis (CFA) in AMOS 19 to assess the psychometric properties of the latent constructs at the store level. Table 2 presents all items used to measure latent constructs, along with their Cronbach's alphas. We simultaneously analyzed construct items corresponding to servicescape quality design perceptions (five items) and time/effort cost perceptions (five items) in a CFA (Anderson and Gerbing 1988) with items constrained to load on their hypothesized factors. In addition, following Podsakoff et al. (2003), we modeled each item to load on a common method factor to isolate the variance potentially attributable to common method bias. As recommended, the CFA included additional multi-item latent constructs that were measured using the same survey instrument but are not included in the hypothesized model estimation. We used the resulting estimated factor loadings and covariances to assess the evidence for convergent and discriminant validity.

The measurement model with common method factor fit the data well. The chi-square for the measurement model was 729.24 (d.f. = 419) and was significant ($p < .01$); however, this statistic is sensitive to sample size and model complexity (Bagozzi and Yi 1988). Thus, consistent with Hu and Bentler (1999), we examined alternative measures of fit that might be more appropriate. The normed fit index for our measurement model was .94, the relative fit index was .92, the comparative fit index was .97, and the root mean square error of approximation was .05. In addition, the inclusion of common method significantly improved the model fit, suggesting that common method variance is appropriately controlled ($\Delta\chi^2 = 260.54$, Δd.f. = 33, $p < .001$). Even after accounting for the common method variance, the estimated loadings for each item are significant, with values exceeding .73 (t-values > 11.56, $p < .01$). The reliability estimates are robust (.94), exceeding the conventional .70 criterion. In terms of discriminant validity, the epistemic correlation between any combinations of latent constructs does not approach unity. Following Fornell and Larcker's (1981) criterion for discriminant validity, the variance extracted for every pair of latent constructs exceeds the highest variance shared. We also estimated a series of CFAs in which the correlations between any two latent constructs were constrained to 1. The constrained models were significantly different from the unconstrained model, providing further evidence of discriminant validity (Anderson and Gerbing 1988). Together, the evidence provides strong support for the validity of the study constructs.

Stage II: Direct Marketing and Objective Service Performance Stock Variables.

To capture both the contemporaneous and lagged effects of direct marketing intensity, we created a stock variable. When capturing the lagged impact of an explanatory variable, one approach is to simply include multiple coefficients for each lagged measure used as a descriptor variable in a regression. This complicates the empirical analysis in at least two ways. Adding "extra" coefficients (1) reduces the power to find effects and (2) could introduce multicollinearity between these lagged variables. Although we expect prior direct marketing to affect future sales, the appropriate lag structure will depend on individual factors, such as the intertemporal reorder frequency. To capture the lagged effects and account for these challenges, we created a stock variable that combines the impact of prior direct marketing on current revenue in a way that puts more weight on more recent direct marketing. Consistent with prior research (Berndt et al. 1995; Schweidel and Knox 2013), we modeled the effects of direct marketing as follows:

$$(1)\quad dmS_{it} = dm_{it} + dm_{it-1}p + dm_{it-2}p^2 + dm_{it-3}p^3 + \ldots + dm_{it-n}p^n,$$

where i = store, t = time, dmS = direct marketing stock variable, dm = weekly dollar investment in direct marketing, p = the decay parameter to be estimated, and n = number of lags.

Because p is constrained to be less than 1.0, the impact of direct marketing from four weeks ago is less (multiplied by p^4) than the impact of direct marketing from last week (multiplied by p^1). The stock variable (dmS_{it}) combines the impact of direct marketing (current and lagged) into one overall variable to be used in further analyses.[2]

We determined the optimal number of weeks in the stock variable empirically by testing a wide range of lag structures. According to interviews with franchisees, the average customer reorder time in this industry is 3–4 weeks. We tested lag structures ranging from 1 to 16 weeks. The Akaike information criterion (AIC) and Bayesian information criterion statistics supported an 8-week lag structure as providing the best fit for the direct marketing stock variable. This approach also accounts for seasonality effects (Franses 2005). Thus, we used the decay parameter optimized with 8 weeks of direct marketing and averaged across the five stores ($p = .91$) to create the stock variable.

We then repeated this process to derive the objective service performance stock variable. To our knowledge, this is the first dynamic operationalization of objective service performance and its effect on sales. This approach is suit-

[2]Although it would be preferable to estimate the decay parameter and stock variable simultaneously during the model estimation (as in Ansari, Mela, and Neslin 2008, who simultaneously estimated their decay parameter within their model using 19,064 observations), we were constrained by both the degrees of freedom available with our data and the need to estimate numerous parameters to test our hypotheses. Therefore, we followed existing research (Narayanan, Manchanda, and Chintagunta 2005). To estimate this model and find the optimal value of the decay parameter for each store, we used the Gauss Newton grid search and a maximum likelihood method in SAS 9.1 to find the best-fitting lag structure by simultaneously considering Equation 1 and $Sales_{it} = \alpha_i + \beta_i dmS_{it} + \gamma_{it}$. This procedure resulted in estimated decay parameters of .91 and .72, which are in line with prior research using stock variables.

able given that (1) there must be a time lag between the service delivery and future purchase for objective service performance to affect consumer choice and subsequent sales revenue and (2) the hypothesized effects of objective service performance imply that given better service, customers may increase their frequency of purchase. Thus, a stock variable would capture any carryover effects of objective service performance on future purchases. Given that current objective service performance is not expected to affect current sales (not many customers order multiple times in the same week), the estimation to find the decay parameter was slightly different in that the lag periods were shifted so that the first period included was at time = t – 1, as follows:

$$(2)\quad servS_{it} = serv_{it-1} + serv_{it-2}q + serv_{it-3}q^2 + serv_{it-4}q^3 + \ldots + serv_{it-8}q^7,$$

where servS = objective service performance stock, serv = objective service performance, and all other notations are as noted previously. We subsequently estimated decay parameter (q) to be .72. We also estimated a model using an alternative measure of objective service performance based on a stock variable created from the standard deviation of the weekly order resolution times to reflect the variability of objective service performance[3] and obtained a similar pattern of results.

Stage III: Model for Hypothesis Testing

To test the hypotheses, we needed a model that could account for the multilevel structure of the data (unit sales, objective service performance, and direct marketing nested within stores) and could model unobserved heterogeneity between the stores. We used a random-parameters model (Greene 2011), which models the effectiveness of marketing variables on sales revenue for each store in the analysis, enables us to capture both between- and within-store effects, and models the impact of the servicescape on the effectiveness of the focal marketing variables as illustrated in Equations 3 (on-site) and 4 (remote). This method enables us to capture the effects of the hypothesized variables on revenue by modeling parameter heterogeneity and capturing random effects.

$$(3a)\quad \text{On-Site Sales}_{it} = \delta_0 + \delta_{1i}servS_{it} + \delta_{2i}dmS_{it} + \delta_{3i}servS_{it} \times dmS_{it} + \delta_4 tv_{it} + \delta_5 bulk_{it} + \delta_6 payroll_{it} + \varepsilon_{it},$$

where $$\varepsilon_{it} = \rho\varepsilon_{it-1} + \nu_{it};$$

$$(3b)\quad \delta_{ki} = \varphi_{0k} + \varphi_{1k}dp_i + \upsilon_{ki};$$

$$(4a)\quad \text{Remote Sales}_{it} = \delta_0 + \delta_{1i}servS_{it} + \delta_{2i}dmS_{it} + \delta_{3i}servS_{it} \times dmS_{it} + \delta_4 tv_{it} + \delta_5 bulk_{it} + \varepsilon_{it},$$

where $$\varepsilon_{it} = \rho\varepsilon_{it-1} + \nu_{it};$$ and

$$(4b)\quad \delta_{ki} = \varphi_{0k} + \varphi_{1k}tep_i + \upsilon_{ki},$$

where i and t denote store and time, respectively; k = 1, 2, 3 and denotes coefficient number in Equations 3a and 4a; On-Site (Remote) Sales = on-site (remote) sales revenue; servS = objective service performance stock and dmS = direct marketing stock, both derived in Stage 1 of the analysis; dp = servicescape quality design perceptions; tep = servicescape time/effort cost perceptions; tv = television advertising; bulk = bulk advertising; payroll = hourly payroll expense; ρ is an autocorrelation coefficient specifying autocorrelated residuals, which can control for time-varying unobserved variables (Jacobson 1990); $\nu_{it} \sim N(0, \sigma^2)$; the coefficients δ_i capture store-specific unobserved heterogeneity within stores; φ represents between-store effects; and $\upsilon_{ikm} \sim N(0, \sigma^2)$ denote store-specific variances.

Equations 3a and 4a show the impact of objective service performance, direct marketing, and the interaction of the two on retail sales. Equations 3b and 4b capture the impact of the servicescape perceptions on the coefficients of these marketing investments. The coefficient δ can change randomly between stores because of unobserved within-store heterogeneity. In turn, φ captures the between-store effects. We conducted estimation with a maximum likelihood procedure and Halton simulations (Greene 2011).

Controls. Although we expect that direct marketing will be the operative variable in our framework,[4] we control for all other marketing communications by including stock variables that capture the weekly GRP of television exposure and the weekly dollar amount invested in bulk advertising (e.g., newspapers, local magazines, coupon door hangers) as controls in the analysis. These marketing communication variables are not directed to specific segments but are sent en masse to both existing and new customers; thus, we do not expect them to interact with measures of objective service performance. We also include the amount spent on hourly payroll as a control variable in the on-site delivery channel. Furthermore, our research design enabled us to control for pricing, which was consistent across all five locations of the retailer in our sample and thus was not explicitly modeled. Similarly, we do not explicitly model competitive efforts; however, our design controls for competition in that all five locations of the retailer were in one metropolitan area facing the same competitive portfolio of retailers.

Endogeneity correction. Although the autocorrelation specification in Equation 3 enables us to control for time-varying unobserved variables (Jacobson 1990), the possibility remains that there are time-invariant (firm-specific) unobservable variables contemporaneously correlated with direct marketing and objective service performance. To address this potential endogeneity in the context of our time-series data, we follow Jacobson's (1990) and Fair's (1970) instrumental variable stepwise approach[5] to correct

[3]We thank an anonymous reviewer for this recommendation.

[4]In our data, the correlation between direct marketing and either of the other two marketing variables is negligible (.06 with TV and –.20 with Bulk).

[5]We appreciate the area editor's suggestion for using this approach.

for it in the model. Accordingly, we first developed instrumental variables for direct marketing and objective service performance by regressing the current value of each variable on its past values lagged one and two periods as well as sales lagged one period. Second, we obtained and saved the predicted value of direct marketing and objective service performance from the first step. Third, we used the predicted values retained in the second step as instruments of direct marketing and objective service performance in estimating Equation 3, correcting for autocorrelation in Equation 4. These instrumental variables are correlated with the current values of the predictor variables, and because they occur temporarily prior, they cannot be influenced by contemporaneous unobservables (Jacobson 1990). The results of our hypothesis testing in Table 3 reflect this endogeneity correction.

Results

Model Fit and Comparison

To assess model fit and robustness of the proposed model (M_h), we conduct a log-likelihood ratio test and AIC comparison with three alternative models: a model with control variables only (M_c), a model that includes only direct effects (M_d), and a model with interactions but no effects of the servicescape dimensions (M_i) (for details of these models, see the Web Appendix). Compared with the model with control variables only (M_c), the likelihood ratio test indicates that the hypothesized model (M_h) provides a significant improvement in fit for both remote ($\chi^2(11) = 78.73, p < .01$) and on-site sales ($\chi^2(11) = 75.14, p < .01$). The AIC indices are also lower for M_h than for M_c in both remote (AIC = 2,860.3 vs. AIC = 2,978.6) and on-site (AIC = 2,712.7 vs. AIC = 2,862.3) service delivery channels. Furthermore, a nested model comparison of M_h and the direct effects (M_d) model based on the likelihood ratio test indicates that M_h provides a significantly superior fit to the data compared with M_d for remote ($\chi^2(7) = 50.08, p < .01$) and on-site sales ($\chi^2(7) = 69.88, p < .01$). This fit is also confirmed by lower AIC indices for M_h compared with M_d for remote (AIC = 2,860.3 vs. AIC = 2,913.4) and on-site (AIC = 2,712.7 vs. AIC = 2,801.2) sales. Similarly, model comparison reveals that M_h constitutes a statistically better fit compared with M_i (which omits the effects of servicescape perceptions) based on the likelihood ratio test for both remote ($\chi^2(5) = 39.71, p < .01$) and on-site sales ($\chi^2(5) = 71.48, p < .01$). This conclusion is also supported by the AIC criteria for remote (AIC = 2,860.3 vs. AIC = 2,895.2) and on-site retail sales (AIC = 2,712.7 vs. AIC = 2,800.3). Drawing on comparisons with multiple alternative model specifications, we conclude that the dynamic interaction of objective service performance and direct marketing contributes significantly to the model, as do the drivers of this interplay, involving servicescape quality design perceptions and time/effort cost perceptions in both remote and on-site service delivery channels.

Hypothesis Testing

Table 3 shows the estimated coefficients from the hypothesized model. To determine that multicollinearity was not a problem in our analysis, we computed variance inflation factors for all predictor and control variables. Because no variance inflation factor (ranging from 1.01 to 3.63) was larger than the conventional threshold of 10, we concluded that multicollinearity was not a threat to the statistical conclusion validity.

TABLE 3
Estimated Coefficients from the Hypothesized Model

Variable	Coefficient	On-Site Service Delivery Channel	Remote Service Delivery Channel
Constant	δ_0	−.19 (1.53)	.01 (.26)
Objective service performance on revenue	δ_1	.13 (.05)***	.19 (.64)
Direct marketing on revenue	δ_2	−.36 (−.43)	1.64 (.78)**
Objective service performance × direct marketing	δ_3	−.06 (.03)*	−.81 (.43)**
Quality Design Perceptions Moderation			
...on objective service performance (servS)	φ_1	−.03 (.01)***	
...on direct marketing (dmS)	φ_2	.10 (.09)	
...on interaction of servS and dmS	φ_3	.01 (.01)*	
Time/Effort Cost Perceptions Moderation			
...on objective service performance (servS)	φ_1		−.09 (.13)
...on direct marketing (dmS)	φ_2		−.30 (.15)**
...on interaction of servS and dmS	φ_3		.16 (.08)**
Control Variables			
TV advertising	δ_4	.06 (.09)	.09 (.07)
Bulk advertising	δ_5	−.00 (.12)	−.02 (.13)
Payroll	δ_6	.55 (.10)***	

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: Levels of significance are based on two-tailed tests. The table reports parameter estimates with standard errors in parentheses. Because variables are continuously measured, the net effects of objective service performance and direct marketing involving a linear combination of ϕ_1, of ϕ_2, and of ϕ_3 must be analyzed to determine their impact (H_2–H_5).

The estimation results for on-site service delivery reveal a significant positive effect of objective service performance ($\delta_{1\text{on-site}} = .13, p < .01$), in support of H_1. We did not find support for H_2 in the on-site service delivery channel, as direct marketing did not significantly affect revenue ($\delta_{2\text{on-site}} = -.36, p > .10$). We find a negative interaction of direct marketing and objective service performance ($\delta_{3\text{on-site}} = -.06, p < .10$), a negative effect of servicescape quality design perceptions on the impact of objective service performance on revenue ($\varphi_{1\text{on-site}} = -.03, p < .01$), and a positive effect of servicescape quality design perceptions on the interactive impact of objective service performance and direct marketing on revenue ($\varphi_{3\text{on-site}} = .01, p < .10$). The marginally negative interaction of objective service performance and direct marketing lends some support for H_3 in the on-site service delivery channel. To further understand this moderation effect, we conducted a Wald test based on the first derivative of retail sales with respect to objective service performance at the average value of servicescape quality design perceptions. The Wald test demonstrates that as direct marketing increases from –2 SD to +2 SD, the effect of objective service performance on retail sales decreases from .05 to –.03 ($p < .05$).

In the remote service delivery channel, we do not find support for H_1, as objective service performance does not significantly affect retail revenue ($\delta_{1\text{remote}} = .19, p > .10$). We do find support for H_2, as direct marketing positively affects retail revenue ($\delta_{2\text{remote}} = 1.64, p < .05$). Our estimation also reveals a negative interaction of direct marketing and objective service performance ($\delta_{3\text{remote}} = -.81, p < .05$), a negative effect of servicescape time/effort cost perceptions on the impact of direct marketing on revenue ($\varphi_{2\text{remote}} = -.30, p < .05$), and a positive effect of servicescape time/effort cost perceptions on the interactive effect of direct marketing and objective service performance on revenue ($\varphi_{3\text{remote}} = .16, p < .05$). The negative interaction of objective service performance and direct marketing indicates strong support for H_3 in the remote service delivery channel. A Wald test based on the first derivative of retail sales with respect to direct marketing at the average value of servicescape time/effort cost perceptions shows that as objective service performance increases from –2 SD to +2 SD, the effect of direct marketing on retail sales decreases from .16 to .12 ($p < .05$), indicating a trade-off effect.

Given the multiple interaction terms involved with H_4–H_7, we formally test these hypotheses using Wald tests. To test H_{4a}, we take the first derivative of on-site sales with respect to objective service performance at the median level of direct marketing. We do not find support for H_{4a-b}: the Wald test indicates that the effect of servicescape quality design perceptions enhances the effect of objective service performance from .00, for low (–2 SD), to .02, for high (+2 SD), and the impact of direct marketing from .002, for low, to .0021, for high, but these effects are not significant. In addition, H_{5a} is not supported, as the servicescape time/effort cost perceptions do not affect the impact of objective service performance (.01 for both high and low time/effort cost perceptions). H_{5b} was partially supported: time/effort cost perceptions increase the effectiveness of direct marketing only when objective service performance is higher than average (specifically, when greater than +.8 SD). Thus, time/effort cost perceptions enhance the impact of direct marketing from .11 to .13 (at +1 SD of objective service performance) and from .08 to .15 (at +2 SD of objective service performance) as time/effort cost perceptions increase from –2 SD to +2 SD (per Spiller et al. 2013), in support of H_{5b} at high levels of objective service performance.

H_6 proposes that design perceptions mitigate the trade-off effects of objective service performance and direct marketing in the on-site delivery channel. We find support for this hypothesis in the significant impact of design perceptions on the random parameter for the interaction of objective service performance and direct marketing ($\varphi_{3\text{on-site}} = .01, p < .10$). Specifically, a Wald test indicates that with high levels of direct marketing, servicescape quality design perceptions elevate the impact of objective service performance from –.01 to .05 as servicescape quality design perceptions increase from low to high. In contrast, with low levels of direct marketing, servicescape quality design perceptions decrease the effectiveness of objective service performance from .02 to –.04 as they increase from low to high. We also find support for H_7 through the significant positive impact of time/effort cost perceptions on the interaction of objective service performance and direct marketing ($\varphi_{3\text{remote}} = .16, p < .05$). Specifically, a Wald test indicates that under high objective service performance, time/effort cost perceptions elevate the impact of direct marketing from .08 to .15 as time/effort cost perceptions increase from –2 SD to +2 SD. In contrast, under low objective service performance, as time/effort cost perceptions increase from –2 SD to +2 SD, they decrease the effectiveness of direct marketing from .28 to .03. In summary, consistent with H_7, time/effort cost perceptions intensify the positive effect of direct marketing when objective service performance levels are high. In contrast, when objective service performance is low, time/effort cost perceptions do not alleviate the trade-off effects (as we expected) and even reduce the net impact of direct marketing.

Therefore, we conclude that servicescape components influence the joint effectiveness of these marketing inputs and, consistent with our hypotheses, that different aspects of the servicescape are important in different service delivery channels. Whereas servicescape quality design perceptions enhance the effectiveness of objective service performance and suppress the trade-off effects of objective service performance and direct marketing (when direct marketing is high) in the on-site service delivery channel (H_6), time/effort cost perceptions increase the effectiveness of direct marketing and alleviate the trade-off effects of objective service performance and direct marketing (when objective service performance is high) in the remote service delivery channel (H_7).

Discussion

This article addresses three important questions that have remained unanswered in diverse streams of marketing research. First, extending theories of integrative response, we conceptualize a model investigating the interplay of

objective service performance and direct marketing and test it using multisource data that include 1,115 weekly retail unit–time observations of objective and archival marketing and performance data combined with responses to a cross-sectional survey of the retailer's customers. Second, motivated by the lack of research on the mechanism through which the environment of the service delivery channels influences marketing effectiveness over time, we conceptualize and empirically demonstrate the disparate role of servicescape factors in shaping the effect of objective service performance and direct marketing in on-site and remote service delivery channels. We find that unique aspects of the servicescape influence marketing effectiveness across specific service delivery channels. When the servicescape better aligns with the customer's needs (in quality design or time/effort cost perceptions), the trade-off effects of direct marketing and objective service performance are mitigated. Finally, whereas prior research has relied on consumer perceptions of the retail experience, which are costly to obtain, this is the first research, to our knowledge, that has linked objective metrics of service performance to retail revenue. Thus, our findings offer practitioners insight into managing the interplay of objective service performance and direct marketing across service delivery channels.

As with all studies, this research has some limitations. First, we used service delivery time as an indicator of objective service performance. Even though our measure is practically relevant and highly appropriate in this context, further research should examine other possible indicators of objective service performance (e.g., order accuracy, product complaints) in different retail settings. Second, we tested the proposed model in one franchise of one industry located within the same city. Extensions to other retail contexts in geographically diverse settings would enhance the generalizability of our findings. Third, we measured direct marketing using the intensity of mailers delivered. Further research would benefit by including measures of the quality as well as the quantity of direct marketing sent out.

Implications for Research

First, this study has implications for retail research and contributes to the body of literature linking investments in service with financial outcomes. The research design and empirical model enabled us to test a theory-based framework that has not been reported in the past: a framework positing that objective service performance affects revenue generation over time. Specifically, support for H_1 in the on-site service delivery channel suggests that objective service performance is more impactful when customers are on-site for the service delivery experience. Zeithaml (2000, p. 67) notes that service investments have not been linked to financial performance for the following reasons:

> First, in much the same way as advertising, service quality benefits are rarely experienced in the short term and instead accumulate over time, making them less amenable to detection using traditional research approaches. Second, many variables other than service improvements (pricing, distribution, competition, and advertising) influence company profits, leading the individual contribution of service to be difficult to isolate. Third, mere expenditures on service are not what lead to profits; instead, spending on the right variables and proper execution are responsible.

Although the current research overcomes these challenges and demonstrates the impact of objective service performance on revenue, the same approach could be extended to investigate the relationship between objective service performance and profitability over time.

This article also advances long-standing models of consumer response to marketing communications. Our mixed support for H_2 suggests that direct marketing intensity is the primary driver in remote service delivery channels. Building on interactive models of advertising response (Smith and Swinyard 1982; Vakratsas and Ambler 1999), we offer the first operationalization to test the dynamic interactive effects of a prior customer experience (objective service performance) with marketing communications (direct marketing). Consistent with our expectations, increasing investments in both objective service performance and direct marketing resulted in diminishing returns. Further research could extend this by incorporating consumer cognitive and affective responses to advertising suggested by Vakratsas and Ambler (1999) through consumer reactions to the advertising message itself, such as consumer attitudes toward the ad. Investigating how the content of the message interacts with objective service performance to determine sales over time will provide further insights into this process.

Third, we identify mechanisms that affect the interplay of objective service performance and direct marketing to generate retail revenue over time in remote and on-site service delivery channels. In the on-site service delivery channel, servicescape quality design perceptions alleviate the negative interactive effects of objective service performance and direct marketing when direct marketing is high. In the remote service delivery channel, however, time/effort cost perceptions are the critical aspect of the servicescape influencing the effectiveness of these marketing investments. To our knowledge, this is the first conceptualization and empirical test of the process through which consumer perceptions of the servicescape interact with other marketing investments to affect the bottom line. With the growth of online service delivery, future researchers should investigate the critical components of the servicescape in an online service delivery channel (e.g., banner ads, pop-ups, loading time), which marketing investments are affected (e.g., e-mail direct marketing, service benefits such as free shipping or other promotions, online personalized shopping assistance), and the interactive impact of these variables on revenue. In addition, researchers would benefit from the development of a taxonomy of service delivery channels and further investigation into which servicescape elements influence ongoing marketing investments within each channel.

Managerial Implications

With marketing departments under increased pressure to justify expenditures on marketing efforts (Rust et al. 2004), our study offers support for investments in service operations at the store level. The empirical support for a direct link between objective service performance and financial

outcomes not only provides scientific support for the use of such measures as benchmarking tools (a common practice in retail industries) but also presents an approach to quantifying daily investments in strategic service initiatives. Our results offer specific implications for managing retail revenue across remote and on-site service delivery channels. Figure 2 plots predicted weekly on-site sales given low (–2 SD; Panel A) and high (+2 SD; Panel B) servicescape quality design perceptions and as a function of (1) objective service performance (x-axis in Figure 2, Panels A and B) and (2) direct marketing when it is either low (25th percentile, solid lines) or high (75th percentile, dashed lines).

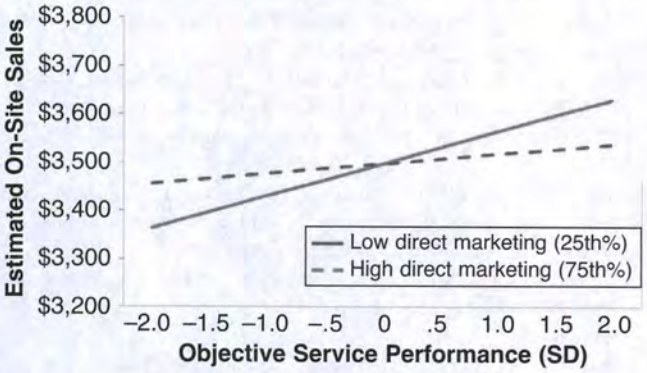
When servicescape quality design perceptions are low (Figure 2, Panel A), the trade-off effect of objective service performance and direct marketing is evident in that greater investments in both (dashed line) result in reduced returns than when focusing only on objective service performance (solid line). In this case, the greatest gains in weekly sales occur through managerial focus on objective service performance alone. Unsurprisingly, direct marketing investments are the primary driver of retail revenue when both servicescape quality design perceptions and objective service performance are low (evident by the left-hand side of the x-axis of Figure 2, Panel A).

When servicescape quality design perceptions are high (Figure 2, Panel B), we observe the elimination of the trade-off between objective service performance and direct marketing, evident by the steeper slope of the dashed line compared with the solid line. In this case, greater returns are achieved by responsibly investing in both objective service performance and direct marketing (far-right point of dashed line) than by investing in only objective service performance (right-hand side of the solid line). If considering improvements to servicescape design (comparing Figure 2, Panel A, with Figure 2, Panel B), our predictions show that the retailer would benefit from (1) elimination of the trade-off effect evident in Panel A (H_6) and (2) greater return from investments in both objective service performance and direct marketing evident by the steeper slope of the dashed line in Panel B than in Panel A.

In the remote service delivery channel, Figure 3, Panel A, reflects low (–2 SD) time/effort cost perceptions, while Panel B shows predictions based on high (+2 SD) time/effort cost perceptions. The dashed lines represent low (–2 SD) levels of objective service performance, and the

FIGURE 2
On-Site Service Delivery Channel Predictions

A: Low Servicescape Quality Design Perceptions



B: High Servicescape Quality Design Perceptions

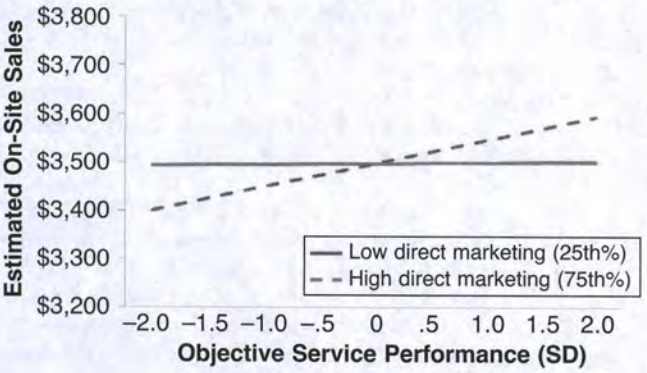
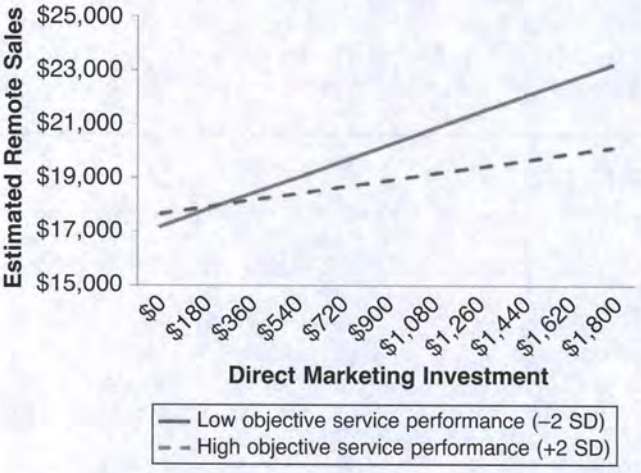
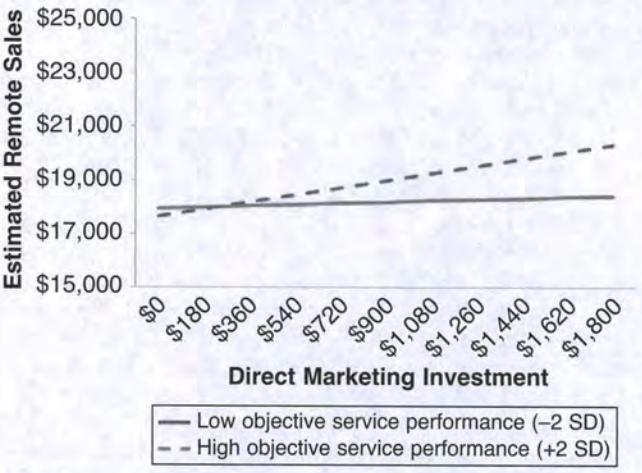


FIGURE 3
Remote Service Delivery Channel Predictions

A: Low Servicescape Time/Effort Cost Perceptions



B: High Servicescape Time/Effort Cost Perceptions



solid lines plot predictions given high (+2 SD) levels of objective service performance.

As with the on-site channel, the trade-off effect (H_3) is evident in Figure 3, Panel A, in the reduced increases in sales with greater investments in direct marketing and objective service performance (right-hand side of dashed line) when compared with low objective service performance (right-hand side of solid line). Panel A shows that when servicescape time/effort cost perceptions are low, managers should invest in direct marketing because this results in the greatest increases to weekly sales. If servicescape time/effort cost perceptions are high (Figure 3, Panel B), the greatest increases to retail revenue occur with investments in both direct marketing and objective service performance (dashed line). This is evidenced by the elimination of the trade-off effect shown in Figure 3, Panel A: the dashed line in Panel B (high objective service performance) increases at a greater rate with larger investments in direct marketing than does the solid line (low objective service performance). In comparing Panel B with Panel A for the remote service delivery channel, we observe that improved time/effort cost perceptions insulate the retailer from the trade-off between objective service performance and direct marketing (H_7).

Thus, support for H_3, H_6, and H_7 across both service delivery channels suggests that retail managers should plan their investments in direct marketing and service performance as a function of the servicescape. To illustrate, instead of investing in direct marketing at all, Five Guys invests in its employees to ensure high-quality, consistent service, a strategy that chief executive officer Jerry Murrell credits for the company's explosive success (Joiner 2012). Our results suggest that Five Guys' strategy is appropriate if consumers have a low perception of the servicescape quality design (Figure 2, Panel A); however, if consumer perceptions are higher, Five Guys is missing out on potential gains by not investing in direct marketing (dashed line in Figure 2, Panel B).

A forward-looking approach to the synergies uncovered by this research could involve employing pliable service delivery channels that enable the customer to tailor the service to the specific goals at hand such that the critical aspects of the servicescape are highlighted for that customer in each stage of the service delivery. Darwill, an Illinois-based printing company, serves as an example of this approach in that it recently added an online portal to augment its service delivery to existing customers (Borden 2009). This online service delivery channel did not replace the firm's direct interaction with customers but rather offered an option for customers to conveniently and remotely access print layouts, reorder, or adjust orders without the need to directly engage a Darwill representative at different stages of the service delivery process. We hope that further research will extend this work by conceptually and empirically elaborating on the intricate dynamic role of objective service performance, direct marketing, and servicescape perceptions in driving bottom-line returns.

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