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In-Store Advertising with Digital Signage

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In-Store Advertising with Digital Signage

Digital signage at the point of sale is emerging as a significant revenue source for retailers and a growing advertising platform for manufacturing brands. Yet, empirical research on its effectiveness remains limited. This study leverages a novel technology and field experimental data spanning 237 advertising campaigns and 30 million shoppers to fill this gap. We find that digital signage increases the likelihood of purchasing featured products by 8.1%. This effect is amplified for hedonic, novel, and low-priced products, as well as for popular brands. It is also stronger on weekends, later in the day, during favorable weather, in crowded stores, for emotional advertising messages, and in the absence of concurrent promotional cues. The impact of digital signage further increases when it is placed in close proximity to the advertised product. Unlike price promotions, digital signage does not affect spending for those who purchase the products. Notably, exposure to digital signage also boosts sales of other products from the same brand and within the same category, without causing purchase acceleration—indicating that it drives incremental consumption. These findings offer new insights into the efficacy of in-store advertising with digital signage and provide actionable guidance for optimizing its use.

Keywords: digital signage, retail media, advertising effectiveness, point of sale, field experiments

Advertising at the physical point of sale (POS) promises enormous reach to the brands that use it and constitutes a highly relevant revenue stream for retailers (McKinsey & Company 2022; Zhu, Cohen, and Ray 2021). By selling their advertising space, retailers achieve profit margins of up to 90% (Boston Consulting Group 2022), compared with an average gross profit margin of around 3% (Repko 2023; Wilson 2023), leading to predictions that this revenue stream will account for $45.3 billion by 2030 (Boidman 2023). For example, Walmart takes advantage of 204 million weekly customer visits to its stores and delivers advertising on an estimated 170,000 digital in-store screens across the United States (Walmart 2023).

Yet even as digital signage at the POS grows more popular, its effectiveness for the manufacturing brands that pay to appear on it is uncertain, and several limitations regarding its accountability remain. Specifically, does digital signage at the POS really increase purchases of featured products? And how strong is this effect across varying conditions? Determining whether online ads are responsible for conversions is already complex (Li and Kannan 2014); establishing causal measures of advertising effectiveness at the POS is even more challenging because physical shoppers do not leave a trail of their behavior (as online shoppers do). This blurriness may help explain why research on digital signage is scarce to date.

To investigate the effectiveness of digital signage at the POS, it is necessary to isolate its effect from the influence of other marketing stimuli, both outside and inside the store (Iyer et al. 2020). Therefore, we adopt a novel method, with the cooperation of a provider company that operates digital signage systems and can match customers' exposure to certain ads with their individual shopping receipts. With this methodology, we effectively rule out shopper-related influences through randomization of participants; we also can exclude the effects of other marketing stimuli by keeping them constant (e.g., same store, same time) or controlling for their potential effects (e.g., price discounts). Specifically, we analyze the impact of in-store video ads on digital signage, using shopping cart radio-frequency identification (RFID) data from 237 field experiments with a total of 30 million shoppers between 2018 and 2022.

Given the importance of digital signage at the POS for both manufacturing brands and retailers, it is critical to understand the factors driving its effectiveness. Although prior research has examined a few contingencies of digital signage, we present a more comprehensive framework that incorporates the role of multiple product-, timing- and campaign-related factors. Our results indicate that exposure to in-store video ads on digital signage increases the purchase probability of these featured products on average by 8.1%. The increase in purchase probability is influenced by different moderators. In-store ads were more effective for hedonic, novel, and low-priced products and for popular brands, on weekends and later in the day, with better weather, in crowded stores, for emotional messages, and without promotional signals. Moreover, placing digital signage closer to the featured product increases its effect. Exposure to digital signage also increases purchases of other products of the same brand and in the overall category but does not lead to purchase acceleration. Therefore, featuring products on digital signage leads to increased consumption. However, unlike price promotions, digital signage does not affect spending by shoppers who purchase the products.

With these findings, we make several novel contributions. First, we are the first to use extensive field data to study the effectiveness of digital signage for the manufacturing brands that pay for the ads and provide high-margin revenue streams for retailers. With our analysis of 237 campaigns, we can specify which products and campaigns are better suited for digital signage. Similar approaches inform recommendations for other advertising channels (e.g., Bart, Stephen, and Sarvary 2014) but not retail media at the POS yet. Second, advertising effects tend to be small, and advertising field experiments often are statistically underpowered (Lewis and Rao 2015), but by pooling data from multiple campaigns, we can ensure sufficient power to detect digital signage effects and simultaneously account for existing and previously overlooked moderators. Third, we test the theoretical assumptions of the two-step process of attention and appraisal from Inman, Winer, and Ferraro (2009) with a new, distinctive technology that stimulates shoppers' attention at the POS. Consequently, we establish several new empirical generalizations and show that several moderators behave differently in our large study than what past research on digital signage has demonstrated in studies with smaller samples.

Our findings aid marketers interested in digital signage on three main fronts. First, depending on their situation, manufacturing brands can better predict whether digital signage is likely to pay off for them (e.g., for which products). Second, once they have decided to invest in digital signage, these brands can use our findings to determine *when* they should run *which* specific campaign to maximize its effectiveness. Third, retailers can use our results to determine how much they charge brand manufacturers for in-store advertising with digital signage and to develop their pricing and price optimization models.

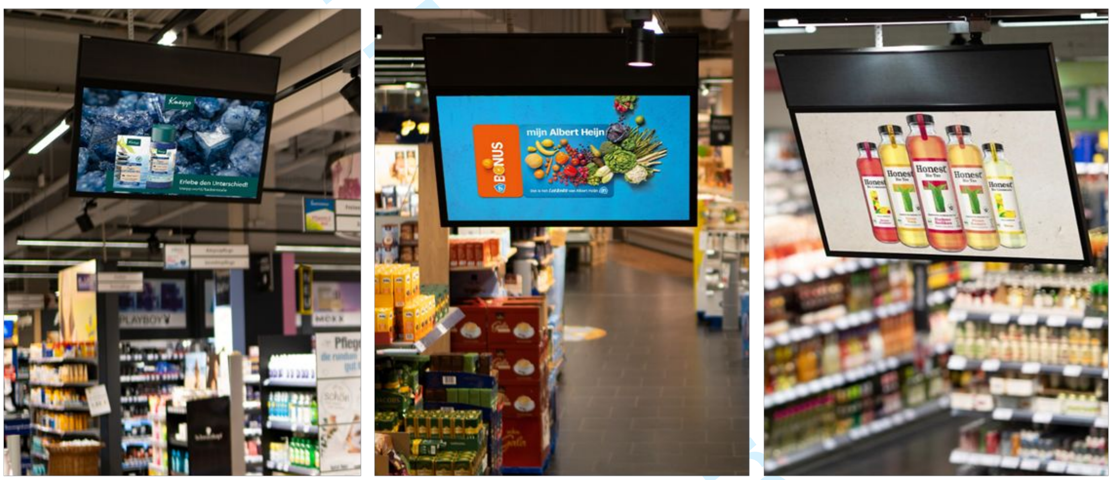
BACKGROUND

Digital Signage and Shoppers' Attention

The digital signage format in this study relies on video screens, located above main aisles in the store (see Figure 1). These screens play audio-visual content controlled by a central computer server and have an attention-drawing impact on customers due to their vividness, defined as the ability of a technology to produce a sensorial rich experience (Nisbett and Ross 1980). Even if it might be used in some cases to enhance the in-store environment (Dennis et al.

2010), digital signage mostly serves to promote products to customers (Nanni and Ordanini 2024). Thus, digital signage represents a *reason to buy instrument*, designed to motivate consumers to purchase a product by communicating certain brand attributes or relevant brand information (Johnen and Schnittka 2020). The proximity of digital signage to products on the shelf enables manufacturing brands to reach shoppers at a highly relevant moment in their purchase decision process, such that it might evoke an inspiration impulse.

Figure 1. Examples of Digital Signage at the Point of Sale



Compared with other in-store advertising instruments, such as non-digital signage or traditional endcaps, digital signage has unique attention-grabbing features that limit the applicability of prior findings. First, digital signage is located in highly frequented aisles in a visual area that captures a lot of attention (Chandon et al. 2009). Shoppers who traverse the aisles in a typical shopping trip pattern with a shopping cart are exposed to its screen for approximately 5–15 seconds (according to the cooperating retailer). Second, the dynamic content on the screens is activated as the shopper's cart approaches the screen, which triggers their attention because the content starts playing only then, rather than repeating endlessly (Khachatryan et al. 2018). Third, the featured videos elicit focal attention with their moving elements (Greenwald and Leavitt 1984). Fourth, directed audio amplifies the effects of the visual elements (Schweiger et al. 2023). These four features clearly differentiate digital signage from other in-store advertising instruments that are located less prominently, provide consistent content on an ongoing basis, feature only static elements, and do not feature audio.

The Digital Signage Business Model

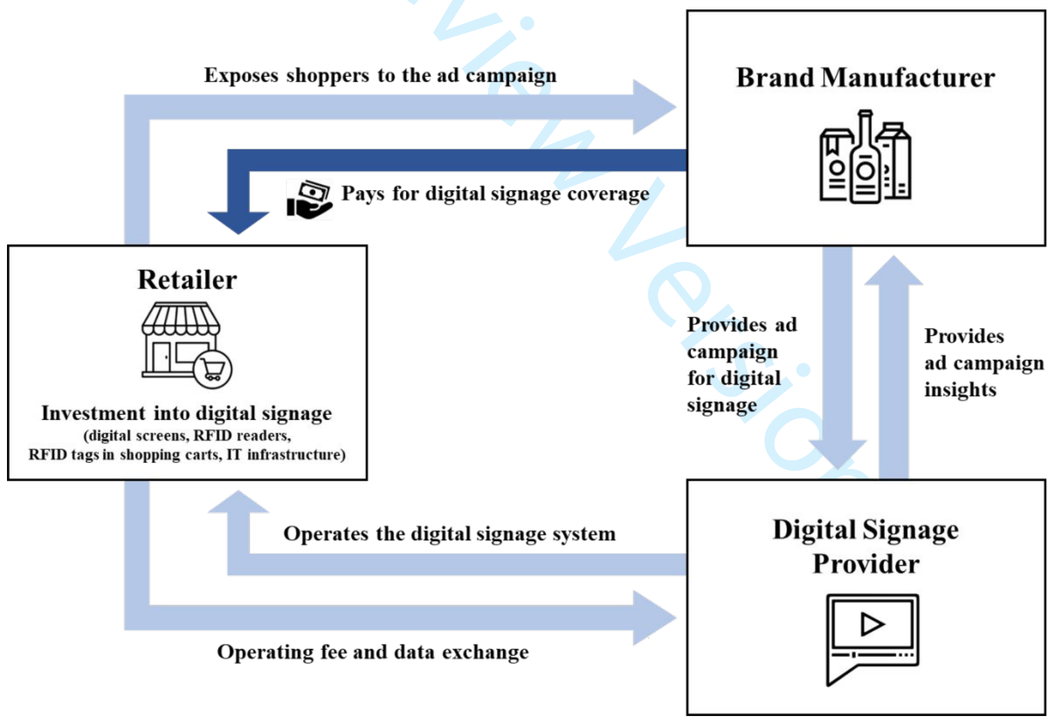
While some retailers use digital signage to promote more purchases (Roggeveen, Nordfält, and Grewal 2016), most retailers realize that retail media can be more profitable if they sell this advertising space to manufacturing brands, offering a new, important revenue stream (Boston Consulting Group 2022; McKinsey & Company 2022). Retailers as varied as Dick's Sporting Goods, Home Depot, Instacart, Lowe's, Kroger, Macy's, Target, Ulta, and Walmart own and operate retail media platforms. In 2023, Walmart earned $3.4 billion from retail advertising, and Target and Instacart each earned more than $1 billion (Gabel, Simester, and Timoshenko 2024).

For this study, we collaborate with a digital signage provider that operates digital screens and creates value for both retailers and manufacturing brands, according to the business model presented in Figure 2.[1] For retailers, it offers a new, high-margin, constant revenue stream, after their initial investment in the necessary in-store technology. For manufacturing brands, it represents a unique in-store advertising instrument and transparent reporting system that can calculate the returns on their ad spending. Thus, even if digital signage operates in retail stores, the actors most interested in its effectiveness are manufacturing brands that pay to promote their brands to shoppers at the POS. As part of its digital signage package, the providers with which

[1] This section and Figure 2 are based on personal communication with the management team of the digital signage provider, confidential reports provided to the brand manufacturers, and insights obtained from the retailer.

we collaborate offers reports of the effects of digital signage on the featured products, other products sold by the same brand, and competitive products. To obtain these reports, the manufacturing brands must provide global trade item numbers (GTINs) for the different product groups that can be recognized from shopping receipts. All of the brands provided GTINs for featured products, but only 14% listed GTINs for their other or competitive products. Thus, brand manufacturers seem primarily interested in the direct impact of digital signage on featured products, and their main request is information about any changes in purchase probability. That is, they want to know if more shoppers exposed to digital signage purchase the featured product.

Figure 2. The Digital Signage Business Model



Note: The dark blue payment path is responsible for profit margins of up to 90% (Boston Consulting Group 2022; McKinsey & Company 2022), compared with an average gross profit margin of around 3% for most retailers (Repko 2023; Wilson 2023).

Table 1. Field Studies on Digital Signage at the Point of Sale

				Attention-Grabbing Features					
Study	**Experiments**	**Shoppers**	**Outcomes**	**Exposure**	**Activation**	**Video**	**Sound**	**Contingencies**	**Key Findings**
Nordfält et al. (2014)	1	62,037	Store-level revenue	—	—	—	—	Type of appeal	Informational content increases and ambience content decreases sales.
Roggeveen, Nordfält and Grewal (2016)	3	183,756	Store-level revenue	—	—	—	—	Store size, type of appeal	The effect of digital signage depends on store size. Only promotional content has a positive effect on sales.
Garaus et al. (2017)	1	200	Individual purchases	—	—	yes	—	Type of appeal	Affective content increases impulse purchases and store loyalty.
Willems et al. (2017)	1	100	Individual purchases	yes	—	—	—	Placement: Entrance vs. register, type of appeal	No differences between the locations and between brand or price appeal.
Garaus and Wagner (2019)	1	88	Individual satisfaction	yes	—	—	—	—	Digital signage at the register increases store satisfaction.
Schweiger et al. (2023)	2	20,632 190,000	Individual purchases, store-level revenue	—	—	yes	yes	Vividness, audio, smell	Inverted U-shaped relationship between vividness and sales. The addition of audio increases sales, whereas smell has no effect.
Nanni and Ordanini (2024)	2	7,009	Individual spending	—	—	—	—	Placement relative to product, type of appeal	No differences between price- and nonprice-related content for discounted products.
Our research	237	29,999,084	Individual purchases	yes	yes	yes	yes	Type of product, brand popularity, product novelty, price of product, price cut, day of week, time of day, weather, crowdedness, type of appeal, promotional signal	Exposure increases purchase probability on average by 8.1%. This effect is higher for hedonic, novel, and low-priced products, for popular brands, on weekends and later in the day, with better weather, for crowded stores, with emotional messages, and without promotional signals.

Notes: We only consider field studies with digital screens in this table. In our empirical setting, we are not able to test all moderators from previous research. Namely, store size is constant in our study, all of our stimuli are vivid with video and sound, and we do not use any olfactory stimuli.

Previous Research on Digital Signage

Extensive studies and empirical generalizations detail mobile and social media advertising effects (Bart, Stephen, and Sarvary 2014; Gordon et al. 2019), but only a handful have examined the effects of digital signage—an important shortcoming, considering that 87% of all U.S. retail sales occur in brick-and-mortar stores (Goldberg 2022). We summarize existing studies of digital signage in Table 1, which represent notable endeavors to contribute to this nascent field. Regarding the potential main effect, Roggeveen, Nordfält, and Grewal (2016) find the effect of digital signage depends on store size; Schweiger et al. (2023) instead indicate a positive effect. The inconsistent findings might stem from the greater vividness of digital screens (e.g., images projected on the floor in Schweiger et al. 2023), implying that studies that feature lower vividness may underestimate digital signage. Other studies prioritize measures of overall sales in the retail store, which is too generic to inform the manufacturing brands that pay for the ads. Furthermore, rather than exposures to certain ads and their specific effects, most studies consider the combined, mutual effects of multiple advertising campaigns on overall outcomes. Finally, because advertising effects tend to be small, some studies likely are statistically underpowered. For example, Nanni and Ordanini (2024) indicate no differential effects of price- and nonprice-related content, but this result might stem from the sizes of their samples.

CONCEPTUAL FRAMEWORK

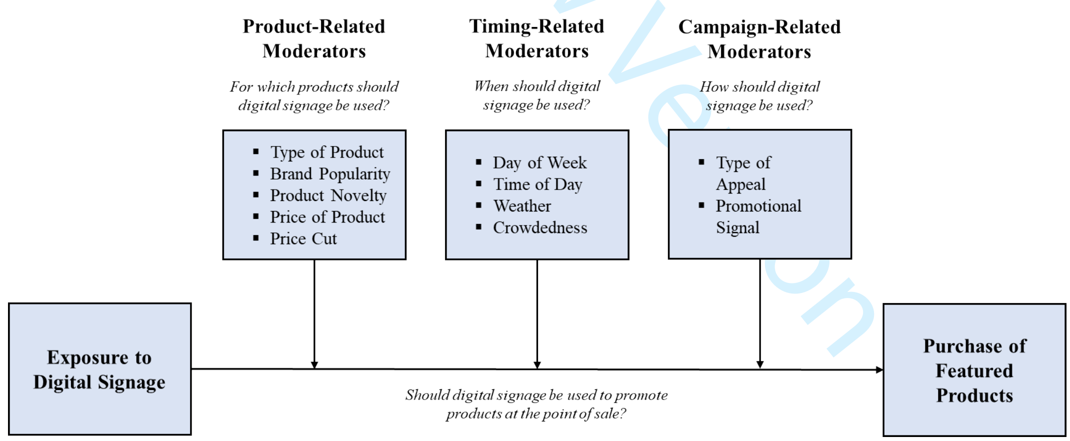
Digital Signage and Purchase Probability of the Featured Products

In-store advertising, such as digital signage, can affect shoppers' decision-making at the POS (Chandon et al. 2009; Hwang and Thomadsen 2015; Zhang 2006). These effects can be explained by the two-step process of attention and appraisal established by Inman, Winer, and

Ferraro (2009). First, digital signage requires the shopper's attention to have any impact. Therefore, greater attention should exert a more salient effect on in-store decision-making. We propose that digital signage elicits attention because the screen locations are in highly frequented aisles (i.e., visual areas that capture a lot of attention), the content on the digital displays gets activated as shoppers approach the screen, videos elicit focal attention with moving elements, and audio amplifies the effects of the visual features. Such attention can be captured by exposure measures, which indicate the high likelihood that shoppers see the advertisement. Second, after shoppers have been exposed to the in-store advertising, they appraise it, which can lead to an advertising response, potentially including impulse buying. Therefore, we expect:

H$_1$: Exposure to digital signage increases the purchase probability of the featured products.

Figure 3. Conceptual Framework



Apart from quantifying the effect of digital signage, we use our conceptual framework as a guiding tool to develop hypotheses on several moderators, as summarized in Figure 3. We consider five product-related features, the type of product (hedonic or utilitarian), brand popularity, whether a new product is featured, the product price, and whether there is a price cut. Because a unique feature of digital signage is its ability to adjust messages dynamically, we also account for four timing-related features. These include the day of the week, the time of the day, the weather, and the crowdedness in the store. Finally, we explore campaign-related factors that advertisers can control, the type of appeal and whether a promotional signal is used. Table 2 summarizes how these moderators link to the two theory-based mechanisms—self-control and variety seeking—that limit or increase the possibility of a response to digital signage. We use self-control and variety seeking to examine product, timing and campaign features Both self-control, an individuals' ability to change their responses (Baumeister 2002), and variety seeking, an individuals' response to the psychological need for stimulation (McAlister and Pessemier 1982), have been used to understand unplanned purchases in prior work (Inman, Winer, and Ferraro 2009; Trivedi 1999). We suggest that when shoppers' self-control is lower and/or variety seeking is high, they are more likely to be influenced by digital signage exposure.

While self-control and variety seeking tendency are psychological states that directly influence how shoppers respond to digital signage, dual processing, circadian rhythm, and experiential shopping are antecedents that shape these psychological states. Central versus peripheral processing reflects how much cognitive effort is involved, which is closely tied to self-control and variety seeking, the circadian rhythm influences energy levels and fatigue, which affect self-control and variety seeking, and experiential shopping reduces self-control and increase variety seeking. Notably, these antecedents are also interrelated. Shoppers may be more tired in the afternoon (due to their circadian rhythm), which can push them toward peripheral processing and make them more receptive to experiential shopping.

Table 2. Mechanisms and Antecedents Underlying the Moderating Effects

	Theoretical Mechanisms		Antecedents			
	Self-Control	Variety Seeking	Dual Processing	Circadian Rhythm	Experiential Shopping	Net Effect
Product-Related Moderators						
H_2: Type of Product	+	+	+		+	+
H_3: Brand Popularity	+	-	+		-	+
H_4: Product Novelty	+	+	-		+	+
H_5: Price of Product	-	-	-		+/-	-
H_6: Price Cut	+	+	+		+/-	+
Timing-Related Moderators						
H_7: Day of Week	+/-	+		+	+	+
H_8: Time of Day	+	+		+	+	+
H_9: Weather	+	+		+	+	+
H_{10}: Crowdedness	+	-	+		-	+
Campaign-Related Moderators						
H_{11}: Type of Appeal	+	+	+		+	+
H_{12}: Promotional Signal	+	+	+		-	+

Notes: Expected effects refer to type of product: hedonic, day of week: weekend, and type of appeal: emotional. The two theory-based mechanisms and three antecedents are overviewed in Web Appendix A. We cannot separate them empirically, but we use them to derive predictions about the moderation effects.

Product-Related Moderators

Type of product. Hedonic products provide emotional and sensory gratification, while utilitarian products serve functional needs (Dhar and Wertenbroch 2000). Exposure to advertising for hedonic products reduces activation in brain regions linked to self-control, and shoppers are likely to indulge in the temptation (Vohs and Heatherton 2000). Similarly, hedonic products show significantly more variety-seeking behavior than utilitarian products (Trijp, Hoyer, and Inman 1996). Moreover, dual-processing such as the Elaboration Likelihood Model (Petty, Cacioppo, and Schumann 1983) can be inferred to suggest that hedonic products are more likely processed through the peripheral route while utilitarian cues are centrally processed, which might make hedonic products more influenced by environmental cues such as digital signage (Dijksterhuis et al. 2008). A similar conclusion can be drawn from research that showcases that experiential shoppers are more likely to pre-plan utilitarian purchases, whereas hedonic purchases are more impulse-driven (Ramanathan and Menon 2006). Thus, digital signage should be more effective for hedonic products that evoke lower self-control and more variety seeking:

H$_2$: Digital signage is more effective for hedonic products than for utilitarian products.

Brand popularity. Brand popularity refers to the level of recognition, admiration, and preference that a brand enjoys among shopper (Keller 2013). Shoppers that encounter more popular brands perceive lower risk, which lowers the self-control and makes purchasing them more impulsive (Sheth and Venkatesan 1968). However, variety-seeking behavior can lead shoppers to intentionally move away from popular brands in pursuit of novelty (Ratner and Kahn 2002). While both mechanisms may be relevant, we expect self-control to dominate in our context because more popular brands require less processing (Campbell and Keller 2003) and hence fit better with peripheral route processing at the POS. Thus:

H$_3$: Digital signage is more effective for more popular brands.

Product novelty. In our study, product novelty is defined as new products recently introduced to the assortment of the retailer. Shoppers exposed to digital signage featuring novel products might anticipate the joy of acquiring something new, leading to less self-control (Rook and Fisher 1995). Novel products further evoke variety seeking, a key experiential shopping motive (Min and Schwarz 2022). The activation of novelty seeking triggers curiosity and increases impulse buying. From a dual-process perspective, however, featuring a novel product on digital signage could evoke processing through the central route, given it is unknown to the shopper (Campbell and Keller 2003). Nevertheless, overall we expect that:

H$_4$: Digital signage is more effective for novel products.

Product price. Shoppers have less self-control and are more tempted to purchase impulsively when the price of the product is low (Cobb and Hoyer 1986). Even when they leave room for impulse items, their spending remains close to their original mental budget, because they work to prevent overspending (Stilley, Inman, and Wakefield 2010). Moreover, a higher price tends to suppress variety seeking (McAlister and Pessemier 1982) while a lower product price minimizes the need for further cognitive elaboration, increases peripheral processing, and thus facilitates impulsive buying (Dijksterhuis et al. 2008). Experiential shoppers are often less price-focused because their motivation stems from hedonic value rather than strict economic rationality (Hirschman and Holbrook 1982). Still, overall we expect that:

H_5: Digital signage is more effective for lower-priced products.

Price Cut. Marketers often use discounts (i.e., price promotions) to trigger impulse purchases (Iyer et al. 2020), though previous research differentiates between promotional signals as proxies for price cuts and actual discounts (Inman, McAlister, and Hoyer 1990). We focus on actual discounts here[2] and discuss promotional signals among the campaign-related moderators. A price cut lowers shoppers' self-control and increases variety seeking because the reduced price minimizes the perceived risk (Kahn and Raju 1991) and offers a strong cue that requires less processing (Dijksterhuis et al. 2008). Experiential shoppers, while willing to pay more, still enjoy the psychological gratification of "getting a good deal" (Darke and Dahl 2003). Thus:

H_6: Digital signage is more effective for products with a price cut.

Timing-Related Moderators

Day of week. Most consumers are busier during the weekdays and take more time to relax and wind-down from work-related stress during the weekend as a break in their routine. When

[2] Actual price discounts are not featured in the content of the digital signage because the same ads typically run for several weeks on the screen, whereas the retailer's actual discounts usually change on a weekly basis.

shoppers are in a busy mindset, a sense of self-importance arises, and self-control increases (Kim, Wadhwa and Chattopadhyay 2019). Self-control lens also offers an opposing rationale, suggesting that when shoppers are pressed for time during the week, less elaborate decision-making is done and self-control is lower. This perspective is in line with Fox and Hoch's (2004) finding that shoppers do more cherry-picking in the weekend when they have more time. Research has demonstrated that consumer are more depleted towards the end of the week (Fritz et al. 2010), and tired consumers seek more variety (Huang et al. 2019). This should make shoppers more receptive to digital signage at the POS on weekends. Thus:

H$_6$: Digital signage is more effective during weekends than weekdays.

Time of day. As the day progresses and many decisions have been made, consumers' level of self-control decreases, leading to more impulsive behavior (Vohs et al. 2018). This is in line with research using the circadian rhythm that shows that consumer stick more closely to their shopping lists and do less variety seeking in the morning (Gullo et al. 2019). These two approaches align with the shopping orientation: when consumers shop early in the morning, they are rather task-oriented while later in the day they follow a more experiential approach, allowing for more stimulation and variety seeking (Kaltcheva and Weitz 2006). Thus:

H$_8$: Digital signage is more effective later in the day.

Weather. Weather conditions affect consumers' daily behaviors; for example, Roehm and Roehm (2005) found that good weather with more sunshine lowers shoppers' self-control and increases their variety-seeking. The circadian rhythm provides an explanation for the influence of weather on shopping behavior (Gullo et al. 2019). When shoppers' arousal is elevated by sunlight, they explore a greater variety of products. Research further demonstrated that experiential shopping is more prevalent when the weather is good (Murray et al. 2010). Thus:

H_9: Digital signage is more effective with better weather conditions.

Crowdedness. In line with Aydinli et al. (2021), crowdedness refers to the experience of social density, defined as the number of people per unit area. Crowded environments are distracting, which reduces shoppers' perceived control (Blut and Iyer 2020). Moreover, in crowded environments, consumers rely on quick intuitive judgements that are in line with peripheral processing rather than central processing (Hock and Bagchi 2018). However, crowded stores may discourage exploration, reducing variety seeking when crowdedness causes stress and leads to simplified decision-making (Machleit, Eroglu, and Mantel 2000). Nevertheless, given that that crowded environments may also heighten the public visibility of consumption choices and increase consumers' variety seeking (Ratner and Kahn 2002), we expect:

H_{10}: Digital signage is more effective when crowdedness is high.

Campaign-Related Moderators

Type of appeal. Messages with emotional appeal rely on drama, mood, and other emotion-eliciting strategies to target the shopper's emotions, whereas messages with informational appeal feature facts, statistics, and logical arguments to convince consumers (Chandy et al. 2001). Taking the self-control lens, emotional appeal is found to be an important driver of impulsive buying, as it disrupts consumers' self-control (Pham 2007). An informational message requires thoughtful, central processing while emotional messages are better suited to peripheral processing (Petty, Cacioppo and Schumann 1983). An emotional appeal is also better suited to address experiential shoppers (Babin, Darden, and Griffin 1994). Finally, the positive affect from emotional appeal can increase variety-seeking (Menon and Kahn 1995). Thus:

H_{11}: Digital signage is more effective with emotional than informational appeal.

Promotional signal. In addition to price cuts, the mere presence of a promotional signal can influence purchasing behavior as they lower self-control (Inman, McAlister, and Hoyer

1990). Promotional signals can provide a final push to purchase a product and make it easier for consumers to justify giving up self-control to attain immediate gratification, which prompts more impulse purchases (Iyer et al. 2020). Promotional signals can trigger variety seeking (Trivedi 1999), minimize the need for cognitive elaboration and increase peripheral processing (Dijksterhuis et al. 2008), and provide psychological gratification (Darke and Dahl 2003). Thus:

H_{12}: Promotional signals increase the effectiveness of digital signage.

FIELD-EXPERIMENTAL METHODOLOGY

Data Collection

Digital signage installed in ten stores, each with five screens (50 in total), provide the data for our field-experimental approach. These stores are in the same region of a Western European country and managed by the same retailer. All the stores carry mainly food and household items, feature a sales space of around 108,000 square feet (i.e., smaller than a typical Walmart supercenter with 182,000 square feet), and earn average annual sales of US$25 million. These stores aim to deliver one-stop shopping, and consumers typically arrive with extensive shopping lists in mind, such that they set aside relatively substantial time for the shopping trip. The screens are attached to the ceiling, located in the middle of main aisles that attract shopper traffic (see Figure 1). After an initial familiarization period, we conducted 237 field experiments on 1,321 different days between 2018 and 2022 (stores are closed on Sundays).[3]

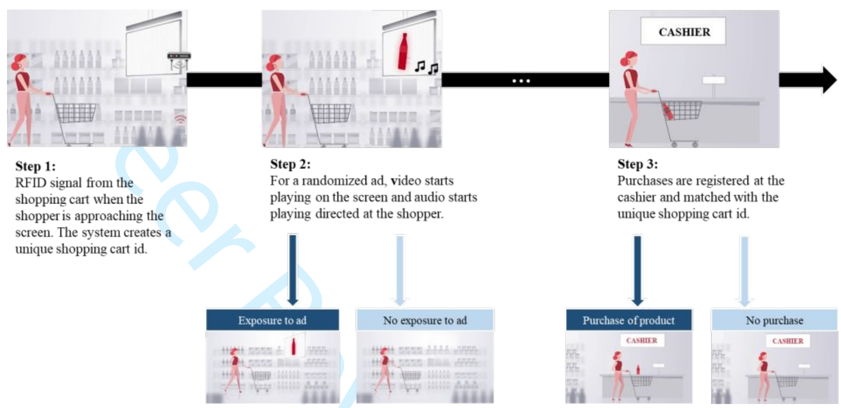
Summary statistics for the 237 campaigns are in Web Appendix B. During the study period, the digital signage system did not engage in targeting for specific ad campaigns, nor was any other targeting or optimization in place. The manufacturing brands pay for a previously

[3] The provider ran these campaigns for its manufacturing brand clients, which developed the ads and chose the campaign duration. We did not influence any aspects of the campaigns or field-testing methodologies used.

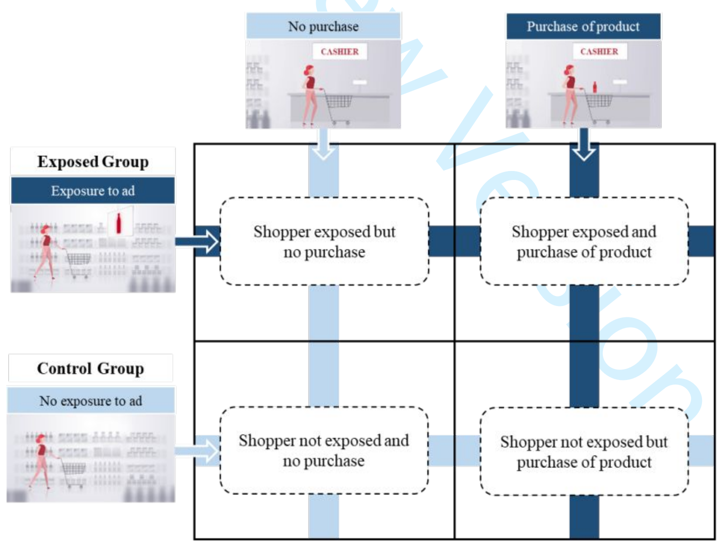
agreed amount of daily shopper exposure, such that the campaigns differ from regular in-store advertising that focuses on store traffic rather than exposure.

Figure 4. Data Collection and Methodology

Panel A: Data Collection with a Unique Shopping Cart ID



Panel B: Methodology for the Exposed and Control Groups



As the depiction of the digital signage system in Figure 4, Panel A, indicates, each campaign's procedure was similar. If not approached by a shopper with shopping cart, the screens constantly play generic and static retailer content, without any sound or references to specific products (e.g., general marketing messages, event information). An advertisement only starts to play if a shopper with shopping cart approaches, within 5 to 10 meters in the same aisle and facing the screen. Then the system gets activated by an invisible RFID tag in the shopping cart, such that it begins playing one of the ads currently installed in the system, according to a random selection. In addition to the video, a directional loudspeaker targets the shoppers. The RFID reader connected to each screen identifies which shoppers with shopping cart were exposed to which ads. At the end of the shopping trip, the RFID tag in the shopping cart links with the cash register to match the exposure with the shopper's receipt, detailing the products purchased (but not any personal information about the shopper).[4] We obtained full access to the scanner data for all stores and the whole study period; for each shopper, we know the exact day and time of the visit, whether they were exposed to any ads, and all items they bought.

Methodology

Our analytical approach follows the same logic as digital advertising testing in prior online field experiments (Bart, Stephen, and Sarvay 2014). Figure 4, Panel B, provides an overview of the experimental conditions. If shoppers approach and experience random exposure to an ad, they enter the *exposed group* for this specific campaign; if they were not exposed or instead saw a different ad, they enter the *control group*. The outcome of interest is purchase probability (i.e., shopper bought a related product, yes/no), for which information was automatically extracted from the receipts.[5] This methodology enables us to isolate the effect of digital signage from other potential determinants, such as shopper traits or resources, through randomization. We also can exclude the effects of other marketing stimuli, outside and inside the store, by keeping them

[4] The cooperating retailer fully respects the privacy of customers, in line with the GDPR.
[5] The GTINs for all products featured in the ad were provided by manufacturing brands, reflecting a standard barcode and numbering system used in global trade to identify a specific product type, in a specific packaging configuration, from a specific manufacturer.

constant (i.e., both groups visit the same store on the same day, so all other advertising effects are constant across groups) or else controlling for their potential effects (e.g., price cuts).

Critically, we measure the intention-to-treat (ITT) and not the treatment itself, because shoppers in the exposed group might not have paid close attention to the screen.[6] This approach might lead us to underestimate the effect of digital signage, but it offers the clear advantage of reflecting the "true effect" of digital signage administered in the field and thereby affirms the ecological value of our studies (Van Heerde et al. 2021). Moreover, using an ITT analysis can reduce the risk of bias due to the systematic imbalance of baseline characteristics that arises in as-treated analyses (Gupta 2011). An as-treated analysis of digital signage specifically would be biased because shoppers who pay attention to in-store advertising are more likely to exhibit greater impulse buying tendencies (Iyer et al. 2020). Noncompliant shoppers would be excluded from such an as-treated analysis, and the digital signage effect then would be biased upward.

ESTIMATION AND RESULTS

Allocation of Shoppers and Model-Free Evidence

Only shoppers with a cart can join the exposed group; shoppers without a cart always get assigned to the control group (because no RFID ever prompts the ads for these shoppers). Acknowledging this systematic bias and the differences in total spending and number of items between such groups (both $p < .001$), we limit our sample to the 10,504,430 shoppers who used shopping carts and frequented the stores during the study period (i.e., purchased at least one item and received a receipt). Each shopper with shopping cart participated in an average of 2.86 field

[6] Due to the limitations of our GDPR-compliant data, we cannot capture shoppers' attention, because such a measurement would require us to visually track all shoppers. However, a recent survey indicates that 71% of shoppers notice digital displays in the store (Vibenomics 2024).

experiments (see Web Appendix C): 39% of these shoppers only joined exposed groups, 36% only entered control groups, and 25% were assigned to both exposed and control groups during the course of their shopping trip. The layout of the stores makes it unlikely that any shopper with a cart could avoid all in-store screens. Thus, the shoppers who were not exposed to any of the ads probably visited at a time that the retailer's algorithm did not play ads or else followed other shoppers, such that they were bystanders to those other shoppers' ad exposure.[7]

We display the model-free effect of exposure in Web Appendix D: Exposure leads to an average purchase probability increase of 50%, and 87% of campaigns had a positive effect. However, this effect may be at least partly driven by the fact that shoppers who spend more time in the shop are more likely to be exposed and more likely to purchase. We carefully address this self-selection effect in our data, as detailed below.

Moderators and Controls

In addition to the experimental data (random exposure to ads) and the scanner data (receipts of purchases of related products), we include data reflecting perceptual and objective measures of the advertised products and ad content, as established by three native-speaking, independent coders who were not familiar with the research question. With access to all 237 ad campaigns and a coding scheme, the coders identified the type of product and type of appeal, as we detail in Web Appendix E. They could watch the campaigns multiple times; they resolved any discrepancies in coding through discussion.

The other moderators were derived from the scanner data, external data sources, or manual coding of objective features. Novel products were those that were recently introduced to the stores, the price of the products was the actual price on the receipt in Euros, and price cuts

[7] Bystanders do not trigger the ad but are exposed to (some part of) it. Any influence of this unnoticed exposure would be included in the control group and therefore make our estimates more conservative.

indicate whether the products were on discount or not at the time of purchase. We extracted the day of the week and time of day from the time stamp of the receipt. To capture the weather, we used the OpenWeather API to obtain sunshine, and we also control for temperature and rain. Crowdedness of the store is measured by the total number of receipts in the hour of the store visit. The coders also gauged brand popularity and the presence of promotional signals.

We include some additional control variables that may affect both attention and purchases. In addition to accounting for potential selection and learning effects, we include the number of items and total spending by each shopper. By noting exposure to different ads, we consider the potential that the focal ad effect could grow weaker. Furthermore, we control for campaign wear-out, the daily count from the first day since the advertising campaign started, as well as the creativity of the ad and any human presence in the ad. We summarize all measures in Web Appendix F, correlations and descriptives are in Web Appendix G.

Addressing Endogeneity Caused by Selection Effects

Two types of potential selection effects may be present in our data: Shoppers might self-select to spend more or less time in the store, and manufacturing brands might self-select into using digital signage with specific content. We address both effects.

Shoppers' self-selection. Shoppers self-select to spend more or less time in the store, and those who spend more time are more likely to pass several screens, trigger ads, and enter one or more exposed groups. Such shoppers also are more likely to be influenced by digital signage, because they seemingly have greater time availability, which increases impulse buying (Iyer et al. 2020). Because this could distort the randomization, we use a Heckman selection model and include an instrument to correct for this self-selection.[8]

[8] Another potential option would be propensity score matching. However, the system is GDPR-compliant, so we are bound by law and have no exogenous information about shoppers that might not be influenced by ad exposure.

In the first stage, we use a probit model to predict shoppers' exposure, based on the total number of items purchased and their total spending, which function as proxies for shopping duration. Shoppers who purchase more items and spend more likely have been in the store longer and passed more different shelves, which increases the likelihood that they trigger the system. We also include an exogenous instrument that influences exposure but is unrelated to the shopper's purchase decision, namely, advertising pressure. Depending on the ad spending of the manufacturing brands, the system calculates daily exposure goals, equal to the overall number of exposures a certain ad should receive each day (i.e., advertising pressure). This target is unknown to shoppers but increases exposure, such that it might influence their purchase behavior but only through increased exposure. Thus, this instrument is both relevant and exogenous. We further control for potential day-of-week, time-of-day, and crowdedness effects on exposure. Specifically, the first-stage probit model is:

(1) $$EXP_i^* = z_i^{EXP}\lambda^{EXP} + \eta_i^{EXP},$$

where EXP_i^* denotes a latent measure with an observed binary response indicator, $EXP_i = I\{EXP_i^* > 0\}$; z_i^{EXP} captures the variables that influence exposure; λ^{EXP} is the unknown parameter vector; and η_i^{EXP} is a random error. We include shoppers' total number of items, total spending (instrumented), day of the week, hour of the store, and crowdedness in z_i^{EXP}. The first-stage regression empirically confirms that advertising pressure is a strong predictor of increased ad exposure (β = 4.800, $p < .001$; χ^2 test = 2,587,571, $p < .001$; see Web Appendix H).

In the second step, we use the estimates of λ^{DPE} and $z_i^{DPE}\lambda^{DPE}$ to compute an inverse Mills ratio (IMR) as a bias correction term for each shopper when predicting purchase probability:[9]

$$(2) \qquad IMR\_EXP_i = \begin{cases} \dfrac{\phi\left(z_i^{EXP}\lambda^{EXP}\right)}{\Phi\left(z_i^{EXP}\lambda^{EXP}\right)} \; if \; EXP = 1, \\ -\dfrac{\phi\left(z_i^{EXP}\lambda^{EXP}\right)}{1 - \Phi\left(z_i^{EXP}\lambda^{EXP}\right)} \; if \; EXP = 0, \end{cases}$$

where Φ is the probability density, and ϕ is the cumulative distribution of the standard normal distribution. We include the exposure correction term when estimating the effects of exposure and the moderators on the purchase probability of the focal product with Equation 4.

Brand manufacturers' self-selection. Only brand manufacturers that expect to benefit use digital signage (as is true of any advertising decision). However, such self-selection is unlikely to bias the estimates, because brand manufacturers rarely decide explicitly about whether to use digital signage or not. Due to the newness of the digital signage system, the digital signage provider worked with a leading national media agency, which offered exposure on digital signage as part of a broader media package to its customers. Thus, the influence of brand manufacturers' strategic decision to the use digital signage is minimal. In addition, the brand manufacturers had no previous direct or indirect experience with digital signage and whether it might be effective for them. The digital signage system we study is the first to be able to capture purchase behavior and effectiveness, and our data collection started with the first campaign run by the system. Thus, different brand manufacturers used the digital signage option for different promotions, featuring well-known and unknown brands, existing and novel products, and

[9] The ad exposure to a specific campaign is randomized. The same shopper may be in the exposed group for one campaign and in the control group for another campaign. This randomization reduces the potential impact of unobserved factors and enhances the credibility of the causal effect of digital signage.

emotional and informational appeals. The effectiveness of certain campaigns was not publicly shared either. The current study represents the first systematic attempt to understand the effects of product, timing and campaign-related characteristics. Finally, we empirically control for a potential learning effect over time (i.e., days since the start of the system) that should capture any informal communication among brand manufacturers.

If brand manufacturers decide to use digital signage though, they might try to maximize its effectiveness. They cannot alter the context, but they have control over the content of the ad campaigns (i.e., type of appeal, promotional signal, creativity, and presence of humans), and this strategic choice is unobservable to us. To correct for potentially endogenous content, we use the control function approach, as detailed in Web Appendix I. We use the average content of other campaigns in the same product categories as instruments:

$$\text{(3a)}\quad TOP_j = \beta_0 + \beta_{1-4}\sum\nolimits_{n=1}^{4} INS_{nj} + \beta_{5-11}\sum\nolimits_{m=1}^{7} CON_{mj} + \varepsilon,$$

$$\text{(3b)}\quad PRS_j = \beta_0 + \beta_{1-4}\sum\nolimits_{n=1}^{4} INS_{nj} + \beta_{5-11}\sum\nolimits_{m=1}^{7} CON_{mj} + \varepsilon,$$

$$\text{(3c)}\quad CRE_j = \beta_0 + \beta_{1-4}\sum\nolimits_{n=1}^{4} INS_{nj} + \beta_{5-11}\sum\nolimits_{m=1}^{7} CON_{mj} + \varepsilon,$$

$$\text{(3d)}\quad POH_j = \beta_0 + \beta_{1-4}\sum\nolimits_{n=1}^{4} INS_{nj} + \beta_{5-11}\sum\nolimits_{m=1}^{7} CON_{mj} + \varepsilon,$$

where TOP_j, PRS_j, CRE_j, and POH_j are the potentially endogenous content variables type of appeal, promotional signal, creativity, and presence of humans, INS_{nj} represents the four instruments, CON_{nj} is a vector of seven campaign-level controls, and ε is the error term. The results are unaffected by the inclusion of the control functions, which suggests unbiased estimates, so we ultimately use the more efficient models (Herhausen et al. 2025).

Model Specification

All variance inflation factors (VIF) are below 3.70 (mean VIF = 1.87). By using robust and clustered standard errors in all analyses, we account for the nested data structure (i.e., the same shopper can appear multiple times in the data set). We median-centered price to acknowledge its high skewness and mean-centered all other predictors for the interaction terms:

$$\text{(4)} \quad logit(PUR_i) = \beta_0 + \beta_1 EXP_i + \beta_{2-12} \sum_{n=1}^{11} MOD_{ni} \times EXP_i + \beta_{13-23} \sum_{n=1}^{11} MOD_{ni} + \beta_{24-29} \sum_{m=1}^{6} CON_{mi} \times EXP_i + \beta_{25-33} + \beta_{35-43} \sum_{p=1}^{9} STO_{pi} + \beta_{44-54} \sum_{q=1}^{11} MON_{qi} + \varepsilon,$$

where PUR_i is the purchase of the focal products by shopper *i* (1 = purchased, 0 = not purchased), EXP_i is shopper i's exposure to the focal campaign (1 = exposed, 0 = not exposed), the vector $MOD_{ni} \times EXP_i$ represents the hypothesized moderating effects, the vector MOD_{ni} represents the main effects of the moderators, the vector $CON_{mi} \times EXP_i$ represents additional interaction effects with controls, the vector CON_{oi} represents the control variables, IMR_EXP_i is the exposure correction term, the vector STO_{pi} contains store fixed effects, the vector MON_{qi} represents the month fixed effects, and ε is the error term.

Hypotheses Tests

Main effect of exposure. Model 1 in Table 3 reveals a positive effect of being exposed to the ad on purchase probability (β = .078, $p < .001$, OR = 1.081). Thus, being exposed to digital signage increases purchase probability by 8.1%[10], in support of H_1.

[10] To ease interpretation, we report relative changes in percent, which refer to multiplicative changes in odds between exposed and not exposed shoppers. For small probabilities like the ones we study odds and probabilities are almost identical (we consider purchase probabilities for specific products among all shoppers in a supermarket).

We ran several robustness tests for this effect, as detailed in Web Appendix J. Whether we estimate the models without selection correction ($\beta = .093$, $p < .001$, OR = 1.097), include total spending instead of residuals ($\beta = .076$, $p < .001$, OR = 1.079), include number of unique SKUs ($\beta = .064$, $p < .001$, OR = 1.066), number of product categories ($\beta = .061$, $p < .001$, OR = 1.063), or number of sectors ($\beta = .059$, $p < .001$, OR = 1.061) instead of number of items, or consider only the subset of shoppers that appear in both the exposed and control groups to control for unobserved differences between groups ($\beta = .090$, $p < .001$, OR = 1.094), the effects remain robust. The exposure effect is also robust when using weekly ($\beta = .077$, $p < .001$, OR = 1.080) or product category ($\beta = .124$, $p < .001$, OR = 1.130) fixed-effects.

Moderating effects. The product type × exposed effect ($\beta = .131$, $p < .001$, OR = 1.139) indicates that the effect of being exposed is stronger for hedonic than for utilitarian products, as we proposed in H_2. The brand popularity × exposed effect ($\beta = .024$, $p < .001$, OR = 1.025) and the product novelty × exposed effect ($\beta = .188$, $p < .001$, OR = 1.206) are positive, in support of H_3 and H_4. The price × exposed effect is negative ($\beta = -.050$, $p < .001$, OR = 0.951), in line with H_5. The price cut × exposed effect is not supported ($\beta = -.006$, $p = .509$, OR = 0.994), in contrast to H_6. In line with our prediction in H_7, the weekend × exposed effect ($\beta = .042$, $p < .001$, OR = 1.043) indicates that digital signage is more effective on the weekend. The time of day × exposed effect ($\beta = .025$, $p < .001$, OR = 1.025) indicates that the exposed effect is stronger later in the day, in support of H_8. We find a positive weather × exposed effect ($\beta = .058$, $p < .001$, OR = 1.060), in support of H_9. The crowdedness × exposed effect is positive ($\beta = .011$, $p < .001$, OR = 1.011), as we predicted in H_{10}. The appeal type × exposed effect is positive ($\beta = .012$, $p < .001$, OR = 1.012), in support of H_{11}. The promotion signal × exposed effect ($\beta = -.101$, $p < .001$, OR

= 0.904) does not support $H_{12.}$ Table 4 summarizes the findings; Figure 5 displays the predicted margins for the moderating effects graphically.

Additional Interaction Effects

We further find a negative wear-out campaign × exposed effect (β = -.025, *p* < .001, OR = 0.975) and a positive learning × exposed effect (β = .034, *p* < .001, OR = 1.034). That is, the same campaign becomes less effective over time, but digital signage generally becomes more effective. We also find negative rain × exposed (β = -.056, *p* < .001, OR = 0.945) and human presence × exposed (β = -.112, *p* < .001, OR = 0.894) effects, providing additional support for the weather effect and suggesting that that human presence in the advertising takes focus away from the product, thereby diminishing persuasion.

We report further analyses in Web Appendix K, including day-of-week dummies, time-of-day dummies, and potential three-way interactions. Results using day-of-week dummies generally confirm our main analyses. The exposure effect is stronger on Saturdays with 11%, and most weekdays do not differ, except Tuesdays with an exposure effect of 13%. This finding might reflect synergies with the retailer's weekly leaflet, which is updated each Tuesday.

A robustness test with time-of-day dummies generally confirms a linear positive effect, with one notable exception: The exposure effect is very high at 8:00 am, reaching 31%, then drops to a minimum around lunchtime, before it increases again in the afternoon and evening. Perhaps shoppers need stimulation first thing in the morning, leading them to engage in more variety-seeking behavior. If consumers need stimulation in the early morning, they may be more (less) receptive to ads for hedonic (utilitarian) products. We find a negative three-way interaction for exposed × time of day × product type (β = -.007, *p* = .001, OR = 0.993), such that the increase during the day is indeed higher for utilitarian products.

Consumers tend to be busier during weekdays, so they may be more receptive to hedonic products. However, we find no three-way interaction for exposed × weekend × product type (β = -.017, p = .338). That is, the product type effects do not differ between weekdays and weekends.

Table 3. Results for the Main Analysis

	Model 1					Model 2				
	β	SE	z	OR	p	β	SE	z	OR	p
Hypotheses										
H_1: Exposed to Digital Signage	.078	.004	18.87	1.081	.000	.050	.009	5.36	1.051	.000
H_2: Type of Product × Exposed						.131	.011	11.72	1.139	.000
H_3: Brand Popularity × Exposed						.024	.005	4.82	1.025	.000
H_4: Product Novelty × Exposed						.188	.012	15.33	1.206	.000
H_5: Price of Product × Exposed						-.050	.007	-7.25	.951	.000
H_6: Price Cut × Exposed						-.006	.010	-0.66	.994	.509
H_7: Day of Week × Exposed						.042	.010	4.39	1.043	.000
H_8: Time of Day × Exposed						.025	.001	21.99	1.025	.000
H_9: Weather × Exposed						.058	.012	5.00	1.060	.000
H_{10}: Crowdedness × Exposed						.011	.001	7.16	1.011	.000
H_{11}: Type of Appeal × Exposed						.012	.003	3.54	1.012	.000
H_{12}: Promotional Signal × Exposed						-.101	.023	-4.49	.904	.000
Additional Interactions										
Wear-out Campaign × Exposed						-.025	.002	-14.60	.975	.000
Learning Effect × Exposed						.034	.002	19.45	1.034	.000
Temperature × Exposed						.014	.008	1.71	1.015	.088
Rain × Exposed						-.056	.016	-3.56	.945	.000
Creativity × Exposed						.002	.004	0.58	1.002	.565
Human Presence × Exposed						-.112	.011	-10.32	.894	.000
Controls										
Wear-out Campaign	-.081	.001	-84.34	.923	.000	-.067	.001	-50.19	.935	.000
Learning Effect	.113	.001	111.05	1.120	.000	.099	.001	77.41	1.104	.000
Temperature	.106	.007	14.68	1.111	.000	.096	.008	11.66	1.101	.000
Rain	.038	.010	3.93	1.038	.000	.075	.013	5.60	1.078	.000
Creativity	-.392	.003	-152.85	.676	.000	-.399	.004	-113.63	.671	.000
Human Presence	-.125	.007	-17.31	.882	.000	-.074	.010	-7.81	.928	.000
Exposed to Different Ads	-.065	.002	-29.36	.937	.000	-.065	.002	-29.06	.937	.000
Number of Items	2.108	.008	263.55	8.231	.000	2.101	.008	260.34	8.172	.000
Total Spending	.189	.007	28.30	1.209	.000	.187	.007	27.44	1.205	.000
Type of Product	-.012	.007	-1.76	.988	.079	-.069	.010	-7.03	.934	.000
Brand Popularity	.290	.003	97.76	1.336	.000	.276	.004	66.26	1.318	.000
New Product	1.734	.008	222.08	5.664	.000	1.646	.011	154.13	5.187	.000
Price of Product	-.436	.004	-112.87	.647	.000	-.418	.005	-84.32	.658	.000
Price Cut	.379	.006	64.56	1.460	.000	.382	.008	48.33	1.465	.000
Day of Week	.115	.006	19.67	1.122	.000	.094	.008	12.14	1.098	.000
Time of Day	.008	.001	12.42	1.008	.000	-.005	.001	-5.50	.995	.000
Weather	.072	.007	9.61	1.074	.000	.038	.010	3.99	1.039	.000
Crowdedness	-.016	.001	-11.99	.984	.000	-.020	.001	-13.59	.980	.000
Type of Appeal	.421	.002	174.55	1.524	.000	.409	.003	135.24	1.505	.000
Promotional Signal	.557	.014	38.66	1.746	.000	.591	.019	30.36	1.806	.000
Selection Correction	-.180	.011	-16.53	.836	.000	-.207	.011	-18.26	.813	.000
Fixed Effects										
Store	included					included				
Month	included					included				
Log-likelihood	-1,455,492.20					-1,454,428.70				
N	29,999,084					29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors, OR = odds ratios. Probit models are in Web Appendix L.

Table 4. Overview of Results and Findings

Hypothesis	Previous Research	Result	Summary of Findings
Should digital signage be used to promote products at the point of sale?			
H_1: Effect of digital signage	mixed effects	✓	Exposure to digital signage increases shoppers' purchase probability of the featured products on average by 8.1%.
For which products should digital signage be used?			
H_2: Type of product	mixed effects	✓	Higher effect for hedonic (vs. utilitarian) products.
H_3: Brand popularity	none	✓	Higher effect for more popular brands.
H_4: Product Novelty	positive effect	✓	Higher effect for novel (vs. existing) products.
H_5: Price of product	none	✓	Higher effect for lower-priced products.
H_6: Price cut	none	×	Effect does not change for products with price cut.
When should digital signage be used?			
H_7: Day of week	none	✓	Higher effect for weekends (vs. weekdays).
H_8: Time of day	none	✓	The effect increases over the day.
H_9: Weather	none	✓	Digital signage is more effective with more sunshine.
H_{10}: Crowdedness	none	✓	Crowdedness increases the effect of digital signage.
How should digital signage be used?			
H_{11}: Type of appeal	mixed effects	✓	Higher effect for emotional (vs. informational) messages.
H_{12}: Promotional signal	mixed effects	×	Promotional signals decrease the effect.

Additional Research Question	Summary of Findings
Does the placement of digital signage relative to the featured products influence its effectiveness?	We find a negative interaction effect between distance to the screen and exposure: Higher effect for products that are closer to the screen.
Do exposed shoppers spend more (or less) on the featured products than shoppers not exposed when they purchase?	Exposure to digital signage does not affect spending for the featured products for those shoppers that purchase.
How does exposure influence switching between the featured products and other products of the same brands, and switching between the featured products and competitive products from other brands?	Exposure to digital signage creates original demand for the focal products. Shoppers exposed to an ad for specific products have a higher purchase probability for other products from the same brand, a lower purchase probability for competitive products, and a higher purchase probability for the overall category.
Does exposure lead to purchase acceleration, i.e., stockpiling of the featured products?	Digital signage does not lead to purchase acceleration and stockpiling of shoppers, in contrast to price discounts.

Notes: We only consider previous research on the effects of digital signage at the point of sale in this table.

Figure 5. Visualization of Moderating Effects

Notes: Grey areas indicate predicted effect were the 95% confidence intervals include zero. We focused on the focal interaction and kept all variables at mean when calculating the results for this figure, with the exception of price which was at its median.

A fit between the type of product and type of appeal, such that hedonic (utilitarian) products are combined with emotional (informational) appeals, could increase the effectiveness of digital signage. However, we find a negative three-way interaction for exposed × product type × appeal type (β = -.033, $p < .001$, OR = 0.967), such that both utilitarian and hedonic products perform best with emotional appeals.

We do find three-way interaction effects between exposure, the type of product, and sunshine (β = 0.071, $p < .001$, OR = 1.073) and between exposure, the type of product, and temperature (β = -0.150, $p < .001$, OR = 0.861) but not for exposure, the type of product, and rain (β = -0.016, $p = .665$). These findings indicate that in our sample, sunshine increase the exposure effect for hedonic products more than for utilitarian products, while the exposure effect does not differ between hedonic and utilitarian products for high temperatures.

ADDITIONAL ANALYSES

The field experiments show that shoppers exposed to digital signage exhibit a higher purchase probability for the featured products, in support of the effectiveness of digital signage. However, they cannot address several managerial questions related to the placement of digital signage and its potential effects on spending, product and brand switching, and purchase acceleration. Therefore, we address the following research questions in further analyses:

- Does the placement of digital signage, relative to the featured products, influence its effectiveness?
- Do exposed shoppers spend more (or less) on the featured products than shoppers not exposed when they make purchases?
- How does exposure influence switching between the featured products and other products of the same brands, as well as switching between the featured products and competitive products from other brands?
- Does exposure lead to purchase acceleration (i.e., stockpiling) of featured products?

Placement of Digital Signage

Previous research summarized in Table 1 found inconclusive placement effects. The ads in our study appear randomly on all screens, regardless of their location, so screen placement should not affect the observed results. Nevertheless, to address the contradicting prior findings, we retrieved digital signage placement data for 183 campaigns (Web Appendix M).[11] We identify a negative interaction effect between distance to the screen and exposure: The average distance of featured products from screens is 30 meters (98.4 feet), and the odds ratios of the logit model indicate that for every 10-meter (32.8 feet) increase in the proximity of a featured product to the screen, the effect of exposure increases by 2%. No other interaction effects are affected when we include distance to the screen though, indicating that the screen randomization worked and that our findings are robust regarding the placement of digital signage.

Spending Conditional on Purchase

In interviews, manufacturing brand representatives indicated that they mainly employ digital signage to attract purchases from shoppers who otherwise would not purchase, but it also might be interesting to determine the effect of digital signage on purchase quantity for the 311,251 shoppers who make at least one purchase of the focal products. As the results in Web Appendix N reveal, we find no effect of exposure on spending ($\beta = .001$, $p = .817$), in line with the missing spending effect of digital signage reported by Nanni and Ordanini (2024). Exposed shoppers purchase the focal products but not more of those focal products. This is in line with the finding that novel products benefit much more from digital signage than existing products.

[11] The cooperating company made a change to its database, such that we were not able to retrieve this information for all campaigns in our sample.

Brand Switching and Product Switching

Previous research has decomposed the effect of price discounts into primary demand effects for the discounted brand, including increased consumption, product switching within the brand, and temporal shifts (which we discuss next), versus secondary demand effects for non-discounted brands (Gupta 1988; Van Heerde, Leeflang, and Wittink 2004). To the best of our knowledge, no such decomposition has been undertaken for in-store advertising. We retrieve data about the effects of digital signage on the focal products, other products of the same brand, and competitive products from 34 campaigns to examine such potential brand switching and product switching, as detailed in Web Appendix O.[12] Our findings suggest three conclusions. First, digital signage at the POS creates original demand for the focal products (increased purchase probability of 10.1%), making it a desirable in-store advertising tool from product managers' perspective. Second, digital signage does not evoke any product switching within the same brand but fosters brand switching to the focal brand. Shoppers exposed to an ad for specific products exhibit a higher probability for purchasing at least one of the other products of the same brand (increase of 8.7%) and a lower probability for purchasing at least one product sold by competing brands (decrease of 12.5%). This evidence indicates that digital signage is desirable from brand managers' perspective. Third, digital signage for particular products have positive spillover effects on the overall category purchase probability (increase of 14.8%), so from retailers' perspective too, the use of digital signage is desirable.

Purchase Acceleration and Stockpiling

We could not track shoppers over time, so we requested additional data from the digital

[12] We relied on the manufacturing brands to obtain GTINs for the product featured in the ad, other products of the same brand, and competitive products, because the categories provided by the retailer did not support such detailed analyses. Unfortunately, most manufacturing brands were only interested in the effect on their focal product.

signage provider to consider the possibility of purchase acceleration, as detailed in Web Appendix P. With a quasi-experimental methodology, we compare 16 stores with and without digital signage over a total of 42 weeks to uncover potential purchase acceleration effects evoked by digital signage for two popular stockpiling products. For the immediate effect of digital signage, we find positive effects for both campaigns (increases of 28.8% and 7.1%), indicating that the presence of digital signage increases the average purchase probability for all shoppers, compared with control stores. We thus affirm the robustness of the positive exposure effect. Regarding the potential purchase acceleration effect, we find no effects for both campaigns, indicating that digital signage does not lead to purchase acceleration or stockpiling.

DISCUSSION

Contributions to Literature

The growth of in-store retail media, together with retailers' increasing awareness that they can monetize contacts with consumers at the physical POS, emphasize the need for a better understanding of digital signage. With this large-scale study, we identify in detail how exposure to digital signage affects purchase behavior at the POS. Using the two-step process of attention and appraisal from Inman, Winer, and Ferraro (2009), we theorize why digital signage works: Digital signage (1) is located in highly frequented aisles in a visual area that captures a lot of attention and provides 5–15 seconds' worth of exposure; (2) is activated when shoppers approach, which triggers attention because the content starts playing and does not just endlessly repeat; (3) features videos that elicit focal attention with moving elements; and (4) complements the visual cues with audio, which amplifies the effects of visual features at the POS. Building on self-control lens, dual process theories, circadian rhythm, and experiential shopping, we specify several moderators of these effects. We test our predictions with a rich data set that encompasses 237 field experiments, involving 30 million participants and a diverse range of products and ad campaigns. We examine whether digital signage is effective for promoting products at the POS, for which products digital signage is best suited, when digital signage should be used, and how digital signage can be leveraged most effectively. We structure our discussion accordingly.

Should digital signage be used to promote products at the point of sale? With a novel method that enables us to attribute ad exposures to individual product purchases across all 237 campaigns, we determine that exposure to a digital signage advertisement at the POS increases purchase probability by 8.1%. Thus, digital signage proves to be an effective tool at the POS that creates original demand for the focal products. Shoppers exposed to ads for specific products exhibit a higher purchase probability for other products from the same brand, a lower purchase probability for competitive products, and a higher purchase probability for the overall category. Moreover, digital signage does not lead to purchase acceleration or stockpiling, in contrast with price discounts (Van Heerde, Leeflang, and Wittink 2004). Whereas price discounts urge shoppers to purchase higher quantities, due to their inherently limited availability, digital signage has no such effects, because it offers no discounts. Digital signage also does not affect the amount of spending on featured products among shoppers who purchase, in line with Wertenbroch's (1998) discussion of the trade-off between self-control failure and purchase quantity rationing. As we find, exposed shoppers purchase, but they do not purchase more.

For which products should digital signage be used? The effects of digital signage vary with the product. Hedonic products, products from popular brands, novel products, and lower-prices products benefit more from digital signage. In contrast, digital signage benefit utilitarian products less; these purchases are often preplanned by shoppers and less likely to be impulsive

(Ramanathan and Menon 2006). Similarly, shoppers' self-control appears to be higher for less popular brands as well as existing and expensive products. We find no interplay with discounts, which is not entirely surprising, considering the mixed effects reported in studies of interactions between price cuts and in-store advertising (Zhang 2006). It confirms that digital signage works, irrespective of price cuts and discounts.

When should digital signage be used? The effects of digital signage vary with the day of the week, time of the day, the weather, and store crowdedness. These effects are stronger on Saturdays and increase over the course of the day, with the highest effects in the evening (though we also observe a notable peak when the store opens at 8:00 am). These findings suggest that being busy and tired of making decisions decreases self-control (Kim, Wadhwa, and Chattopadhyay 2019). Digital signage is also more effective in better weather and when the store is crowded, suggesting that in these conditions, shoppers' self-control is lower.

How should digital signage be used? The appeal type and presence of promotional signals inform the effects of digital signage. They are greater with emotional rather than informational appeals, perhaps because the former disrupt shoppers' self-control (Pham 2007). Non-promotional content increases the effect of digital signage, in line with Grewal et al.'s (2023) findings that inspirational content is more effective than deal-oriented content for in-store advertising. Perhaps such content activates shoppers' inspiration, which in turn lowers their self-control. This further suggests that digital signage may be more effective for shoppers who are innovative and interested in trying new products. These type of shoppers are very different from deal seekers who generally adhere more strictly to their shopping plans (Bellenger and Korgaonkar 1980). Moreover, actual price cuts (r = -.197) as well as promotional signals (r = -

.107) are less often used for novel products. When established products are discounted or promoted, traditional signs may actually be more effective than digital signage.

Collectively, these insights provide novel evidence pertaining to retail media and the effects of in-store advertising. To the best of our knowledge, this study is the first to gather extensive field data to determine the effectiveness of digital signage for the manufacturing brands that pay for the ads. By analyzing 237 separate campaigns, we determine which product, timing, and campaign features are best suited for digital signage. This study quantifies the extent to which the effectiveness of the campaigns differ, which is particularly useful for this relatively new advertising channel, because it reveals the ranges of possible outcomes that marketers can expect. In addition, advertising effects tend to be small, and advertising field experiments often are statistically underpowered (Lewis and Rao 2015). By pooling data from multiple campaigns, we simultaneously consider existing moderators and uncover previously overlooked ones related to the digital signage effect. In turn, we establish several new empirical generalizations about the outcomes of digital signage at the POS. Finally, we test the theoretical assumptions of the two-step attention and appraisal process (Inman, Winer, and Ferraro 2009) by exploiting a new, distinctive technology that stimulates shoppers' attention at the POS. In so doing, we show that some moderators behave differently in our large study than what past research on digital signage has demonstrated in studies with smaller samples. As a consequence, we shed new light on some mixed effects from previous studies on some moderators, as we summarize in Table 4.

Table 5. Implications and Research Directions

Research Question	Implications	Research Directions
Should digital signage be used to promote products at the point of sale?	▪ On average, exposure to digital signage increases the purchase probability of the featured product by 8.1% ▪ Exposed shoppers purchase not more but more exposed shoppers purchase. ▪ Positive spillover effects on other products from the same brand and the overall category, negative effects on competitive products. ▪ No purchase acceleration and stockpiling effects.	▪ Further research should combine exposure to digital signage with loyalty card data and explore the effect on long-term outcomes such as brand preferences. ▪ Research in a country with lower privacy standards should identify bystanders and determine the treatment intensity variation of the effect (e.g., capture the effect of actual exposure and duration of attention). ▪ Future research should examine the effect of digital signage on shoppers using baskets. ▪ The present study focuses on supermarkets. Further research should explore the effect of digital signage in other types of physical stores.
For which products should digital signage be used?	▪ The more hedonic the product, the stronger the effect from digital signage. ▪ The effect from digital signage is stronger for more popular brands. ▪ The effect from digital signage is stronger for novel products. ▪ The effect from digital signage is stronger for lower-priced products. ▪ Price cuts do not interact with the effect of digital signage.	▪ The present study focuses on products only. Further research should explore the effects of digital signage on general message effectiveness. ▪ Featured products were all available in the store. Further research should explore whether digital signage might backfire if products are out of stock or not directly available at the POS. ▪ Future research should explore the interplay of digital signage and other in-store marketing tools at the POS, such as endcaps.
When should digital signage be used?	▪ Digital signage is more effective on weekends. ▪ The effect of digital signage increases over the day with highest effects in the evening. ▪ Digital signage is more effective with better weather (i.e., more sunshine, less rain). ▪ Higher crowdedness increases the effect of digital signage.	▪ The present study shows a higher effect on Tuesdays, where the weekly product flyer is distributed. Further research should explore whether responses to other in-store advertising is also affected by the weekly product flyer. ▪ The present study indicates an increase in effectiveness in the early morning. Further research should explore whether responses to other in-store advertising also are higher at this time. ▪ Research should explore the role of in-store temperature in altering the responses to digital signage.
How should digital signage be used?	▪ The effect of digital signage is greater with emotional messages compared to informational messages. ▪ Promotional signals decreases the effect of digital signage.	▪ The present study focuses only on selected campaign features. Further research could explore additional features of ads, such as humor, the presence of celebrities, or the facial features of humans. ▪ Digital signage in the present study does not optimize the presentation of ads. Further research should use optimization algorithms based on our findings and additional insights (e.g., type of shopper) to make digital signage more efficient.

Managerial Implications

This research offers timely insights for brand manufacturers and retailers engaged in digital signage by providing concrete evidence about the outcomes they can expect from in-store advertising, as well as recommendations related to features that alter its effectiveness. We provide these implications, along with some research directions, in Table 5. Digital signage appears to be an effective in-store advertising tool to increase the purchase probability of featured products, but its effectiveness varies with the product, the timing, and the campaign. Managers can take advantage of digital signage at the POS and our findings in diverse retail environments by installing digital screens and connecting impressions to specific ads with purchase behavior. While the connection means may need to be adapted for different retail formats–using shopping baskets, mobile phone tracking, or face recognition instead of shopping carts–the general logic remains the same: Once it is possible to connect the different data sources, managers can measure and alter their campaigns to maximize effectiveness. To provide actionable insights, we use our results to define the value of digital signage for all stakeholders: brand manufacturers, retailers, and digital signage providers (see Web Appendix Q).[13]

Implications for brand manufacturers. For brand manufacturers, digital signage has positive effects on the featured products and their other branded products; using these effects, we can calculate advertising elasticity as the percentage change in a brand's sales due to a 1% change in the brand's digital signage investment. We find an elasticity of .18 for digital signage—50% greater than the empirical generalizations of short-term brand advertising elasticities equal to .12 reported by Hanssens (2015) and Sethuraman, Tellis, and Briesch (2011). Proximity to the POS and the unique features of digital signage likely induce these higher

[13] We sometimes use industry averages rather than actual values in the reported calculations, reflecting the non-disclosure agreements with the digital signage provider, the brand manufacturers, and the retailer.

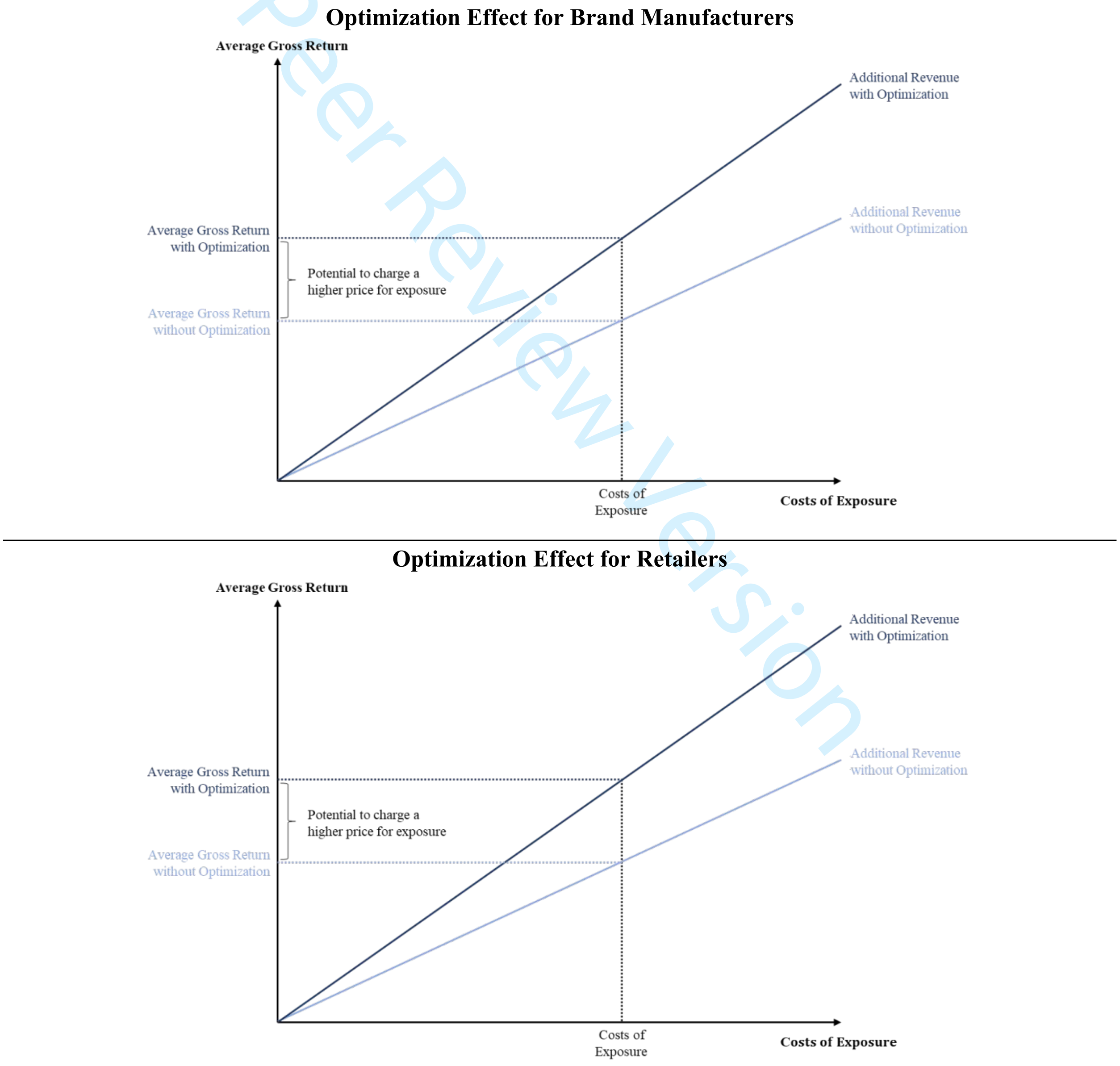
elasticities. Considering the costs of exposure (i.e., how much a brand manufacturer pays for 1,000 exposures) and additional sales minus the retailer's markup, we estimate that a brand manufacturer would earn an average gross return on investments in digital signage of 21%.

Implications for retailers. For retailers, digital signage requires investments in the digital screens, RFID readers, and RFID tags in shopping carts, along with the IT infrastructure. The retailer in our study equipped each store with five digital screens, five RFID readers at the screens, a RFID reader at every cashier, and RFID tags in all shopping carts. To recoup these investments, the retailer needs the additional revenue from the average gross profit margin of around 3% on additional purchases (Repko 2023; Wilson 2023) and the advertising revenue from the brand manufacturers (i.e., the money the retailer receives per 1,000 exposures). Considering the ongoing costs of the system, the digital signage installation in our study would break even for the retailer after approximately 1-2 years, depending on the percentage of campaigns for their own brand and for manufacturing brands, and provide additional profit afterwards. Our data further suggest that 87.7% of the additional revenue stems from digital signage and only 12.3% from the additional sales, confirming the value of digital signage. These insights can be used by retailers to determine how much they charge brand manufacturers for in-store advertising with digital signage and to develop their pricing and price optimization models.

Implications for digital signage providers. Advertising delivery through digital signage has not been optimized yet. During our study period, the digital signage system did not use any targeting, nor did any other targeting or optimization efforts take place. This scenario benefited our effort to identify identifying causal effects, but it also indicates that the vast potential for optimization has not been tapped. The digital signage provider with which we collaborated plans to leverage our findings to target shoppers and optimize the effectiveness of its digital signage.

Increasing the effectiveness of digital signage will enhance the average gross return for brand manufacturers' expenditures, allow the retailer to charge a higher price for exposures to digital signage, and shorten the time until investments in digital signage pay off, as displayed in Figure 6. Thus, all relevant stakeholders in Figure 2 would befit from optimization effects.

Figure 6. Optimization Effects for Brand Manufacturers and Retailers



Notes: The value of digital signage is calculated in Web Appendix Q.

Limitations and Further Research

Continued research should address the limitations and expand the scope of the present research. The digital signage system we studied fully complies with the most stringent privacy requirements, such that we were not able to identify individual shoppers. Continued research should strive to account for individual differences in self-regulation or add loyalty card data to explore the effects on acquisition and retention. Our findings of a positive interaction effect of product novelty and a negative interaction with the wear-out effect offer initial evidence that digital signage might work better for customer acquisition than retention. We also could not identify bystanders, that is, shoppers who did not trigger the ad but received (partial) exposure to it. We assigned these shoppers to the control group, which leads to more conservative estimates. Nor could we examine treatment intensity variations, such as exposure duration or shoppers' distance from the digital signage. Research in a country with different privacy standards might attempt to identify bystanders and determine such treatment intensity effects.

We investigated many moderators in our study; considering the multiple testing problem, we recommend treating the findings with care, despite the many robustness tests we conducted. Because the RFID technology relies on shopping carts, we had to exclude all shoppers without carts, but shoppers with carts could differ systematically from shoppers who instead use baskets. Our data collection took place in retail stores in a Western European country and focused on featured products. The effects of digital signage might differ in in different settings, and we encourage future research to examine digital signage in other types of stores and other countries to generalize our results. Going beyond the focus of our study, future research might further explore whether our results generalize to display and banner ads in online retail settings.

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WEB APPENDIX
In-Store Advertising with Digital Signage

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Web Appendix A. Theoretical Mechanisms and Antecedents for the Moderating Effects

This web appendix describes the two theory-based mechanisms and the three antecedents, and how these are related to digital signage. We draw on these mechanisms and antecedents in the conceptual development section.

Self-Control

Self-control, or self-regulation, explores how individuals choose between competing alternatives—for instance, the tension between an immediate temptation and a long-term goal (Rachlin 1974). This framework, rooted in both psychology and economics, conceptualizes decision-making as a conflict between impulsive desires and deliberate goal-oriented behavior. Although consumers generally act in a manner that aligns with their long-term objectives, they are often affected by temporary needs or desires that may interfere with longer-term goals (Gollwitzer 1999). Baumeister (2002) illustrated that indulging in short-term impulses reflects a failure of self-control. When self-control is strong, individuals prioritize higher-order goals; however, as this resource diminishes due to time or contextual factors, momentary desires often take over. Consequently, self-control is a limited resource that is influenced by the situation.

In a shopping context, consumers' self-control resources are constantly challenged (Hoch and Loewenstein 1991; Vohs and Faber 2007). As shown by Iyer et al (2020), marketing stimuli at the point-of-sale influence self-control that in turn can shift consumers' focus more to impulsive purchases to indulge in immediate temptation. Therefore, and in line with Inman, Winer, and Ferraro (2009), we use a self-control to examine product-related, timing-related and campaign-related features that limit or increase the possibility of a response to digital signage.

Variety Seeking

Variety seeking describes consumers' intrinsic tendency to pursue novel and diverse experiences, often independent of dissatisfaction with prior choices (McAlister and Pessemier 1982). This behavioral phenomenon is driven by psychological mechanisms such as boredom, curiosity, and the desire for stimulation or self-expression (Kahn 1995). From a marketing perspective, variety seeking is particularly relevant in contexts that increase arousal or disrupt routine choice behavior—such as the point of sale.

Emotional and contextual factors like positive affect (Menon and Kahn 1995) or social visibility (Ratner and Kahn 2002) can enhance consumers' preference for change and novelty. Promotional signals—such as "new" tags, limited-time offers, or price discounts—can further stimulate variety seeking by lowering the perceived risk of trying unfamiliar options and justifying deviation from habitual behavior (Trivedi 1999). In a POS environment, visual and promotional stimuli such as digital signage can activate variety-seeking tendencies by making alternatives more salient and emotionally appealing. Thus, we use a variety seeking to examine product-related, timing-related and campaign-related features that limit or increase the possibility of a response to digital signage.

Dual Processing

Dual processing theories of persuasion, especially the Elaboration Likelihood Model (ELM), distinguish between two routes of information processing: a central route (systematic, analytical) and a peripheral route (heuristic, intuitive). The early work by Petty, Cacioppo and Schumann (1983) posits that when consumers are highly involved or motivated and able to think about a message, they engage the central route, scrutinizing the message's arguments and product-related information. In contrast, when involvement or cognitive resources are low, the peripheral route dominates, and consumers rely more on general cues and simple inferences rather than elaborating on the content of the message.

According to the ELM, shopping is a typical situation in which consumers choose products more unconsciously and are more likely to rely on the peripheral route of persuasion (Dijksterhuis et al. 2008). Shopping in the physical store is characterized by a high level of distraction in a dynamic and visually engaging environment where consumers' primary focus is on shopping tasks or navigating the store, not on deeply processing information. Consequently, when the ability or willingness to focus on a message is limited (e.g. due to limited mental capacities in crowded shopping environments), people resort to peripheral processing. In such contexts, dynamic stimuli on digital signage act as powerful peripheral cues. Digital signage frequently features video, animation, or flashing graphics intended to capture attention within seconds and cut through the noise to catch a shopper's attention (Mackenzie 1986). As a result, shoppers may elaborate only minimally on the communication provided by digital signage and rely more on cues in the ads or make simple inferences about the merits of the products.

Circadian Rhythm

Human behavior and decision-making processes are dynamic over time and are found to fluctuate by our biological rhythm. The most commonly recognized rhythm is the circadian rhythm which refers to the "biological clock" regulating our body's 24-hour cycle (Liang et al. 2024, Terman and Terman 1970). However, these cycles extend beyond a single day. In addition to the circadian rhythm, humans also experience longer-timespan rhythms, such as the weekly (circaseptan) rhythms and even seasonal or yearly rhythms. These rhythms regulate physiological arousal, alertness, and even cognitive function across each rhythm. During every rhythm, consumers cycle through a diverse set of transitions, such as the sleep-wake and rest-active transitions. These physiological shifts are associated with changes in the human body, for example, the increase in alertness due to increasing cortisol levels in the morning, as well as sleepiness in the evening when melatonin levels rise. Prior literature in the marketing domain has demonstrated the importance of these rhythms and how they influence working memory (Hasher, Lustig, and Zacks 2007; Myers et al. 2014); arousal (Gullo et al. 2019); and sensory sensitivity and memory (Hornik and Miniero 2009; Huang et al. 2019).

In the retailing context, it is recognized as an important factor influencing consumer behavior throughout the day or week. While the overall goal of digital signage is to influence consumers at the point-of-sale, their reaction to these stimuli could be different depending on their rhythm. Therefore, we use a circadian / circaseptan rhythm to examine the timing-related features that limit or increase the possibility of a response to digital signage.

Experiential Shopping

Experiential shopping is one aspect of consumers' shopping orientations. Previous research has identified many different motives for why consumers go shopping (Arnold and Reynolds 2003; Büttner, Florack, and Göritz 2013; Ganesh, Reynolds, and Luckett 2007). All different motives can be narrowed down to two different shopping motives, focused on either tasks or experiences (Gupta and Kabadayi 2010; Kaltcheva and Weitz 2006). When consumers enter a shopping situation with a task-focused orientation, their main goal is to fulfill their utilitarian shopping value and shop as efficiently as possible. As a consequence, consumers in this orientation stick more to their shopping lists, shop faster and stick closer to the mental budget that they had in mind before shopping with less room for impulse buying. When consumers shop under an experiential orientation, their aim is to maximize hedonic shopping value by seeking stimulating environments and products. In this orientation, consumer are more likely to try out new products, spend more money than they had anticipated on and have a larger variety in their shopping basket. While consumers' shopping orientations are partly based on individual differences, prior research showed that situational factors may also influence which shopping orientation is activated. For example, a stimulating store environment may activate a more experiential orientation (Childers et al. 2001), whereas a situation surrounded by heavy factual information might activate more task-focused shopping orientations.

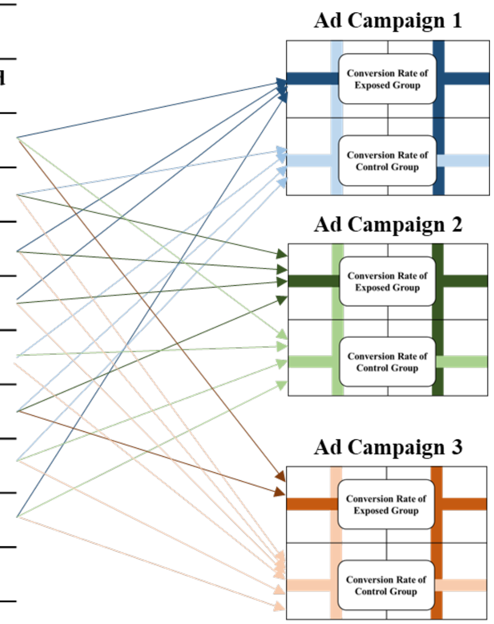
In a retailing context, digital signage can serve as a way to activate an experiential shopping orientation. By transforming the shopping environment through dynamic multimedia displays and interactive content, digital signage creates a sensory-rich, immersive experience that stimulates consumers' curiosity. The visually engaging nature of digital displays encourages exploration and spontaneous decision-making, leading consumers to deviate from shopping lists and predetermined budgets. Therefore, we use an experiential shopping orientation as a potential explanation for product-related, timing-related and campaign-related features that limit or increase the effectiveness of digital signage.

Web Appendix B. Campaign Summary Statistics

Number of campaigns	237
Mean number of participants per campaign (SD)	126,578 (231,136)
Mean campaign length in days (SD)	20.22 (31.77)
Percentage of campaigns with human presence	20.25%
Percentage of campaigns with promotional message	6.75%
Percentage of campaigns with novel product	54.01%
Brand popularity	
Unknown brand	9.70%
Small national brand	15.61%
Large national brand	63.71%
Large international brand	10.97%
Percentage of campaigns per product category	
Appliances	7.82%
Beverages	18.83%
Dairy products	3.50%
Food	58.92%
Hygiene products	5.64%
Magazines	1.43%
Newspapers	3.86%
Mean type of product	
7-point scale (1 = utilitarian, 7 = hedonic)	4.56 (0.42)
Mean type of appeal	
7-point scale (1 = informational appeal, 7 = emotional appeal)	2.81 (2.13)
Day of week	
Monday	14.85%
Tuesday	13.77%
Wednesday	13.70%
Thursday	17.86%
Friday	18.51%
Saturday	21.31%
Time of day	
Morning (8 am to 12 pm)	17.41%
Midday (12 pm to 3 pm)	27.94%
Afternoon (3 pm to 7 pm)	33.73%
Evening (7 pm to 11 pm)	20.92%

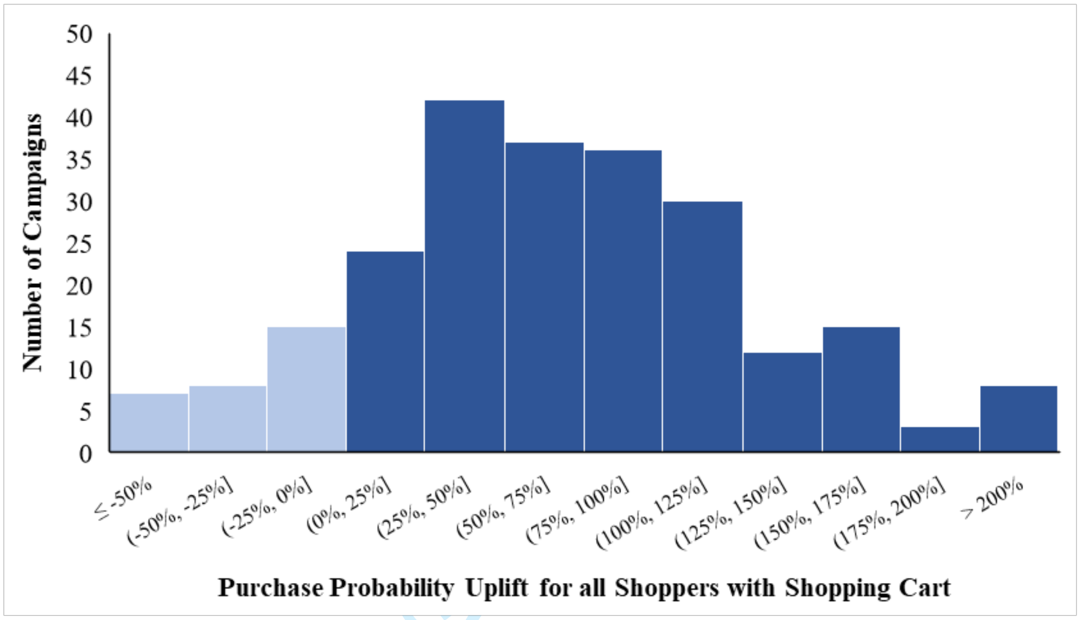
Web Appendix C. Allocation of Customers to the Experimental Groups

			Ad Campaign 1		Ad Campaign 2		Ad Campaign 3	
Shopper Id	Items	Spending	Exposed	Purchased	Exposed	Purchased	Exposed	Purchased
1000001	27	37.98	1	1	0	0	1	0
1000002	45	102.12	0	0	1	1	0	1
1000003	9	7.45	1	0	1	0	0	0
1000004	36	56.04	1	0	1	0	0	0
1000005	7	8.55	0	1	0	1	0	1
1000006	4	1.96	0	0	1	0	1	0
1000007	3	7.56	0	0	0	0	0	0
1000008	18	25.34	1	0	0	1	0	1
…								



Note: This is a fictitious example of group allocation in case three different ad campaigns are running simultaneously on digital signage at the same time in the same store. Each shopper that triggers the system gets randomly exposed to one of the ad campaigns, and each shopper can get exposed to more than one ad campaign. Thus, the same shopper can be in the exposed group for one ad campaign and in the control group for another ad campaign.

Web Appendix D. Model-Free Evidence



Notes: We calculate purchase probability uplift caused by exposure to digital signage with:

$$Uplift = \frac{CR_{Exposed\ Group} - CR_{Control\ Group}}{CR_{Control\ Group}}$$

where CR is the conversion rate. We report the intention-to-treat effect of the 237 campaigns because we include shoppers in the exposed groups that may have not paid attention to the digital signage (only shoppers with carts are considered).

Web Appendix E. Details and Examples for the Expert Coding

To distinguish among different types of products, we captured the utilitarian versus hedonic nature of the products featured in the ads with a six-item measure, using a seven-point scale developed by Noseworthy and Trudel (2011). The first three items capture utilitarian characteristics: “I consider the advertised product to be: functional/not functional, effective/not effective, necessary/not necessary.” The other three items capture hedonic characteristics: “not fun/fun, not enjoyable/enjoyable, not delightful/delightful.” The utilitarian items were reverse coded, so a higher score means a more hedonic focus.

Examples for Type of Product (Utilitarian vs. Hedonic)

Shower Gel (Utilitarian Product)

The shower gel has a utilitarian focus, as its primary role is to clean the skin and remove dirt, sweat, and impurities.

Chocolate Bar (Hedonic Product)

The chocolate bar has a hedonic focus, as it provides pleasure, emotional satisfaction, and an experiential feeling.

To distinguish the different types of messages, we captured the type of appeal shown in the ad with a measure used by Akpinar and Berger (2017). The coders received the following instruction: “Some ads use an emotional appeal, where the ad is designed to appeal to the receiver’s emotions by using drama, mood, music and other emotion-eliciting strategies. They use warm appeals, or an emotional drama versus lecture format, contain pleasant pictures, contain likeable music and sources. In contrast, some ads use an informational appeal, where the ad is designed to appeal to the rationality of the receiver by using objective information describing a brand’s attributes or benefits. They use brand-differentiating message, a benefit appeal, an attribute appeal, factual versus feeling appeal, and a large number of message arguments.” They then rated the ads on how they relate to these two appeals on a 7-point scale (1 = informational appeal, 7 = emotional appeal).

Examples for Type of Appeal (Informative vs. Emotional)

Toothpaste (Informative Appeal)

The appeal speaks to the rationality of the consumer by using objective information about the toothpaste and its benefits.

Soda (Emotional Appeal)

The appeal uses an emotion eliciting strategy by showing a person drinking a refreshing drink in sunny weather.

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Web Appendix F. Measurement of Variables

Variable	Measurement
Dependent Variables	
Purchase	Global Trade Item Number of the exposed product matched with the bought products from the receipt (0 = not bought, 1 = bought)
Independent Variable	
Exposed to Digital Signage	Automated recognition of RFID tag in shopping trolley by the screen (0 = not exposed, 1 = exposed; see Figure 4 in the manuscript)
Moderators	
Type of Product	Noseworthy and Trudel (2011), see Web Appendix E
Brand Popularity	Categorial measure (0 = unknown brand, 1 = small national brand, 2 = large national brand, 3 = large international brand)
Product Novelty	Novel product dummy (0 = established product, 1 = novel product)
Price of Product	Average price of featured product (in Euro)
Price Cut	Discount dummy (0 = no discount, 1 = discount)
Day of Week	Weekend dummy (0 = weekday, 1 = weekend; Ahlbom et al. 2023)
Time of Day	Hour of day (8 am to 11 pm, opening hours of the stores; Kanuri et al. 2018)
Weather	Sun in percentages of the day (Li et al. 2017)
Crowdedness	Total number of receipts (in 100) within the hour of the store visit (Aydinli et al. 2021)
Type of Appeal	Akpinar and Berger (2017), see Web Appendix E
Promotional Signal	Promotion dummy (0 = no promotion in ad, 1 = promotion in ad; Roggeveen, Nordfält, and Grewal 2016)
Controls	
Wear-Out Campaign	Count from the first day since the advertising campaign started, in units of 10 days (Roggeveen, Nordfält, and Grewal 2016)
Learning Effect	Count from the first day since digital signage started, in units of 100 days (Roggeveen, Nordfält, and Grewal 2016)
Temperature	Temperature in Celsius, in units of 10 degrees (Li et al. 2017)
Rain	Rain, in units of 100 millimeters (Li et al. 2017)
Creativity	Three-item scale from Tucker (2014)
Human Presence	People dummy (0 = no people in ad, 1 = people in ad; Li and Xie 2020)
Exposed to Different Ads	Count of different ads
Total Items	Count of total items on the receipt
Total Spending	Saved residuals from regressing total items on total spending

Web Appendix G. Descriptives and Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Purchase																						
2. Exposed	.021																					
3. Type of Product	-.040	-.035																				
4. Brand Popularity	.006	-.126	.489																			
5. Product Novelty	.022	-.036	.029	-.156																		
6. Price of Product	-.041	-.087	.004	.022	-.063																	
7. Price Cut	.013	.007	-.019	-.026	-.197	.159																
8. Day of Week	.000	.001	-.009	-.002	-.004	.007	-.040															
9. Time of Day	.006	-.004	-.039	-.002	.035	-.022	-.016	.002														
10. Weather	.000	.014	.016	.029	.062	-.062	-.060	.033	.045													
11. Crowdedness	-.018	-.303	-.041	.077	-.035	.181	.033	.132	-.045	-.141												
12. Type of Appeal	.042	-.013	.019	.118	-.443	.007	.187	-.008	.003	-.006	.032											
13. Promotional Signal	.001	.019	.035	.190	-.107	-.015	-.046	-.018	-.057	.017	-.081	-.082										
14. Wear-out Campaign	-.026	.040	-.023	-.185	.191	-.031	-.007	.027	.052	.012	-.030	-.144	-.104									
15. Learning Effect	.046	.257	-.041	-.155	-.057	-.128	.098	-.055	-.139	-.042	-.366	.097	.211	-.071								
16. Temperature	.008	.114	-.136	-.021	.008	-.160	-.050	-.016	.114	.059	-.255	.089	.015	.146	-.072							
17. Rain	.002	.022	-.008	-.026	-.027	.002	-.025	-.111	-.021	-.186	-.007	-.024	-.022	-.003	.070	.044						
18. Creativity	-.018	-.099	.262	-.039	.061	-.073	-.024	-.019	-.041	-.008	.029	.369	-.064	-.052	.033	-.119	-.023					
19. Human Presence	.012	-.055	-.121	-.108	.136	.070	.002	.023	.085	.112	-.015	.373	-.220	.329	-.292	.202	-.048	.272				
20. Exposed to Different Ads	.011	-.243	.006	.020	.039	.139	.080	-.027	.014	-.018	.491	.129	.037	-.052	-.079	-.200	-.061	.038	.006			
21. Number of Items	.064	.082	-.001	-.005	-.001	.011	-.003	.026	.007	-.013	.022	-.011	-.012	.004	-.046	.000	.006	.002	.022	-.018		
22. Total Spending	.007	-.001	-.005	-.010	-.021	.001	.010	.000	-.020	-.021	.018	.008	.010	-.011	.063	-.025	.014	.000	-.034	-.004	-.012	
Mean	0.01	0.45	4.60	1.51	0.24	3.39	0.18	0.21	15.18	38.36	4.97	4.40	0.04	3.19	6.77	85.91	5.44	1.67	0.59	2.75	0.25	0.01
SD	0.10	0.50	0.46	1.02	0.43	4.08	0.38	0.41	3.51	0.34	4.05	1.96	0.18	3.45	3.58	0.59	0.23	1.34	0.49	1.73	0.20	0.25

Notes: N = 29,999,084. Given the sample size, almost all correlations are significant at $p < .001$ (two-tailed).

Web Appendix H. First Stage Regression for Shoppers' Self-Selection

	Model 3: Without Instrument				Model 4: With Instrument			
	β	SE	z	p	β	SE	z	p
Predictor								
Number of Items	.006	.000	481.96	.000	.007	.000	549.74	.000
Total Spending	.000	.000	22.81	.000	-.000	.000	-15.96	.000
Crowdedness	-.125	.000	1,726.15	.000	-.117	.000	1,516.11	.000
Instrument								
Advertisement Pressure					4.800	.003	1,558.54	.000
Fixed Effects								
Day of Week	included				included			
Time of Day	included				included			
Log-likelihood	-18,818,595				-17,524,810			
N	29,999,084				29,999,084			

The results indicate a significant improvement in model fit when advertisement pressure is included as a predictor in the model, $\chi^2(1) = 2{,}587{,}571$, $p < .001$.

Web Appendix I. Addressing Brand Manufacturers' Self-Selection

Brand manufacturers may try to maximize the effectiveness of digital signage with the content of the ad campaigns, and this strategic choice is unobservable to us. To correct for the potentially endogenous content, we use a control function approach where we include the fitted residuals and inverse Mills ratios (IMR) for the potentially endogenous content variables (Petrin and Train 2010). For the continuous variables type of appeal and creativity, a first-stage linear regression computes the fitted residuals, and in the second-stage regression the fitted residuals are added, and the instruments are excluded from the model. For the binary variables promotional signal and human presence, a first-stage probit regression computes the IMR, and in the second-stage regression the IMR is added, and the instruments are excluded from the model.

For the first-stage regressions, we need to find instruments that correlate with the respective content variables, but not with the unobserved determinants of the outcome (that form part of the error term); that is, we must find instruments that meet the relevance and exclusion restrictions (Rossi 2014). We use the average content of other campaigns in the same product categories as instruments (e.g., Becker, Wiegand, and Reinartz 2019; Germann, Ebbes, and Grewal 2015). The products in our sample belong to 16 different categories, as specified by the retailer. In terms of relevance, we argue that the focal brand manufacturer faces similar market conditions as their peers within the product category. Thus, similar communication and content approaches should make the instruments relevant. We further argue that the instruments meet the exclusion restriction because the specialized company operating the digital signage system only allows one brand manufacturer per product category at a time, such that other brand manufacturers' ad campaigns that run at a different time should not interfere with the focal campaign. In addition, it is unlikely that competitors exchange about the success of their ad campaigns or would visit the retail stores to observe shoppers' reactions to the content of competitors. Therefore, the instrument should be uncorrelated with the omitted variables related to the strategic behavior of brand manufacturers.

We report the first stage results from Equation (3) in Table I1. For type of appeal, creativity, and human presence the (pseudo) R^2's for all three first-stage regressions significantly improve with the addition of the respective instrument ($\Delta R^2_{\text{type of appeal}} = .12$, $\Delta R^2_{\text{creativity}} = .16$, and $\Delta R^2_{\text{human presence}} = .22$). All instruments are significantly related to the focal constructs ($\beta_{\text{type of appeal}} = .988$, $p < .001$; $\beta_{\text{creativity}} = .910$, $p < .001$; and $\beta_{\text{human presence}} = 12.691$, $p = .002$). The corresponding F-statistics and $\chi 2$-statistics for these instruments all exceed the threshold value of 10 (Stock, Wright, and Yogo 2002; $F_{\text{type of appeal}} = 249.53$, $p < .001$; $F_{\text{creativity}} = 83.65$, $p < .001$; and $\chi 2_{\text{human presence}} = 10.02$, $p = .002$). Unfortunately, the instrument for promotional signal is weak ($\chi 2_{\text{promotional signal}} = 0.20$, $p = .65$), probably caused by the low percentage of ad campaigns that use promotional signals (i.e., 5% of campaigns).

Nevertheless, the controls and other instruments can explain 51% of the variance in promotional signals, indicating that we are able to capture a large exogenous part of the potentially endogenous effect of promotional signals on purchase probability.

The second-stage results including the control functions are reported in Table I2. Given that the inclusion of the control functions does not significantly alter the parameters of the content variables (all effects are directional similar and all estimates are relatively similar) and the strong, untestable assumptions underlying any instrumental variables we use the more efficient model for hypotheses testing (Ebbes, Papies, and van Heerde 2022).

Table I1. First Stage Results for the Control Functions and Inverse Mills Ratios

	Model 5: Type of Appeal				Model 6: Promotional Signal			
	β	SE	z	p	β	SE	z	p
Controls								
Brand Popularity	.260	.084	3.09	.002	2.473	.866	2.86	.004
Type of Product	.502	.148	3.40	.001	-2.186	1.220	-1.79	.073
Novel Product	-.404	.180	-2.24	.026		–		
Price of Product	-.012	.023	-0.53	.593	.114	.174	0.65	.515
Type of Appeal		–			-.389	.261	-1.49	.136
Promotional Signal	-.370	.215	-1.72	.087		–		
Creativity	.159	.066	2.43	.016	-.140	.260	-0.54	.590
Human Presence	1.721	.186	9.24	.000	-1.269	.833	-1.52	.128
Instruments								
$INS_{Type\ of\ Appeal}$	.988	.063	15.80	.000	2.096	.935	2.24	.025
$INS_{Promotional\ Signal}$	-1.785	.817	-2.18	.030	-2.373	5.275	-0.45	.653
$INS_{Creativity}$	-.186	.116	-1.61	.110	2.345	1.268	1.85	.064
$INS_{Human\ Presence}$	-1.604	.328	-4.89	.000	-7.134	4.656	-1.53	.125
(Pseudo) R^2		0.889				0.506		
N		237				237		

	Model 7: Creativity				Model 8: Human Presence			
	β	SE	z	p	β	SE	z	p
Controls								
Brand Popularity	-.054	.086	-0.62	.533	.305	.355	0.86	.391
Type of Product	.272	.151	1.80	.073	-1.262	.624	-2.02	.043
Novel Product	.914	.172	5.31	.000	2.701	1.190	2.27	.023
Price of Product	.020	.023	0.87	.383	.163	.129	1.26	.206
Type of Appeal	.160	.066	2.43	.016	1.893	.464	4.08	.000
Promotional Signal	-.114	.217	-0.53	.600	.793	.606	1.31	.191
Creativity		–			-.312	.265	-1.18	.239
Human Presence	.301	.219	1.38	.170		–		
Instruments								
$INS_{Type\ of\ Appeal}$	.029	.091	0.32	.753	-2.164	.640	-3.38	.001
$INS_{Promotional\ Signal}$	.356	.828	0.43	.667	8.385	4.695	1.79	.074
$INS_{Creativity}$	.910	.100	9.15	.000	-.568	.499	-1.14	.255
$INS_{Human\ Presence}$	-.458	.345	-1.33	.186	12.691	4.010	3.16	.002
(Pseudo) R^2		0.565				0.780		
N		237				237		

Notes: β = unstandardized coefficients, SE = standard errors. Novel product is excluded from the promotional signal model because of collinearity (i.e., none of the campaigns for novel products uses promotional signals).

Table I2. Second Stage Results including Control Functions

	Model 9				
	β	SE	z	OR	p
Hypotheses					
H_1: Exposed to Digital Signage	.081	.004	19.42	1.085	.000
Controls					
Wear-out Campaign	-.104	.001	-85.99	0.902	.000
Learning Effect	.130	.001	104.89	1.138	.000
Temperature	.131	.007	17.71	1.140	.000
Rain	.056	.010	5.67	1.058	.000
Creativity	-.228	.006	-36.13	0.796	.000
Human Presence	-.031	.021	-1.48	0.970	.139
Exposed to Different Ads	-.036	.002	-16.38	0.965	.000
Number of Items	2.111	.008	253.16	8.258	.000
Total Spending	.177	.007	25.43	1.193	.000
Type of Product	-.103	.013	-8.15	0.902	.000
Brand Popularity	.574	.006	91.53	1.775	.000
New Product	1.207	.010	121.16	3.342	.000
Price of Product	-.396	.004	-110.59	0.673	.000
Price Cut	.361	.006	60.32	1.434	.000
Day of Week	.124	.006	20.74	1.131	.000
Time of Day	.007	.001	10.03	1.007	.000
Weather	.034	.008	4.49	1.035	.000
Crowdedness	-.024	.001	-18.09	0.976	.000
Type of Appeal	.266	.004	66.61	1.305	.000
Promotional Signal	.464	.016	28.30	1.590	.000
Selection Correction	-.219	.012	-18.94	0.803	.000
Control Functions					
$CF_{\text{Type of Appeal}}$	.058	.006	9.20	1.060	.000
$CF_{\text{Promotion}}$	.068	.002	29.44	1.071	.000
$CF_{\text{Creativity}}$	-.178	.007	-24.41	0.837	.000
$CF_{\text{Human Presence}}$	-1.184	.012	-96.74	0.306	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,392,191.60				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Web Appendix J. Robustness Tests

Table J1: Results without Selection Correction

	Model 10				
	β	**SE**	**z**	**OR**	**p**
Hypotheses					
H_1: Exposed to Digital Signage	.093	.004	22.87	1.097	.000
Controls					
Wear-out Campaign	-.080	.001	-83.99	0.923	.000
Learning Effect	.118	.001	121.29	1.125	.000
Temperature	.106	.007	14.74	1.112	.000
Rain	.034	.010	3.48	1.034	.000
Creativity	-.402	.003	-159.84	0.669	.000
Human Presence	-.129	.007	-17.81	0.879	.000
Exposed to Different Ads	-.064	.002	-28.91	0.938	.000
Number of Items	2.174	.007	315.90	8.796	.000
Total Spending	.188	.007	28.07	1.207	.000
Type of Product	.012	.007	1.75	1.012	.081
Brand Popularity	.283	.003	95.08	1.327	.000
New Product	1.738	.008	221.85	5.684	.000
Price of Product	-.442	.004	-115.42	0.643	.000
Price Cut	.374	.006	63.93	1.454	.000
Day of Week	.127	.006	22.03	1.136	.000
Time of Day	.008	.001	11.46	1.008	.000
Weather	.071	.007	9.55	1.074	.000
Crowdedness	-.027	.001	-25.82	0.973	.000
Type of Appeal	.426	.002	176.51	1.530	.000
Promotional Signal	.549	.014	38.10	1.731	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,455,666.40				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table J2: Results with Total Spending

	Model 11				
	β	SE	z	OR	p
Hypotheses					
H_1: Exposed to Digital Signage	.076	.004	18.51	1.079	.000
Controls					
Wear-out Campaign	-.081	.001	-84.31	0.923	.000
Learning Effect	.115	.001	112.36	1.121	.000
Temperature	.105	.007	14.57	1.111	.000
Rain	.038	.010	4.01	1.039	.000
Creativity	-.392	.003	-152.96	0.676	.000
Human Presence	-.126	.007	-17.46	0.881	.000
Exposed to Different Ads	-.066	.002	-29.63	0.937	.000
Number of Items	2.093	.009	238.76	8.110	.000
Total Spending	.000	.000	3.54	1.000	.000
Type of Product	-.014	.007	-1.97	0.986	.049
Brand Popularity	.289	.003	97.76	1.336	.000
New Product	1.731	.008	221.79	5.647	.000
Price of Product	-.435	.004	-112.74	0.647	.000
Price Cut	.378	.006	64.51	1.460	.000
Day of Week	.115	.006	19.69	1.122	.000
Time of Day	.008	.001	12.33	1.008	.000
Weather	.071	.007	9.51	1.073	.000
Crowdedness	-.015	.001	-11.68	0.985	.000
Type of Appeal	.421	.002	174.31	1.523	.000
Promotional Signal	.556	.014	38.61	1.744	.000
Selection Correction	-.182	.011	-16.76	0.833	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,456,036.00				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.
We also updated the first-stage regression for shoppers' self-selection by including total spending instead of residuals.

Table J3: Results with Number of Unique SKUs

	Model 12				
	β	SE	z	OR	p
Hypotheses					
H1: Exposed to Digital Signage	.129	.004	31.79	1.138	.000
Controls					
Wear-out Campaign	-.080	.001	-83.92	0.924	.000
Learning Effect	.108	.001	106.68	1.114	.000
Temperature	.106	.007	14.73	1.112	.000
Rain	.072	.009	7.81	1.075	.000
Creativity	-.369	.002	-148.33	0.691	.000
Human Presence	-.085	.007	-11.91	0.919	.000
Exposed to Different Ads	-.061	.002	-27.85	0.941	.000
Number of Unique SKUs	.015	.000	134.02	1.015	.000
Total Spending	.190	.008	25.30	1.209	.000
Type of Product	-.052	.007	-7.59	0.949	.000
Brand Popularity	.303	.003	102.63	1.354	.000
New Product	1.705	.008	222.25	5.500	.000
Price of Product	-.422	.004	-112.72	0.656	.000
Price Cut	.374	.006	64.32	1.454	.000
Day of Week	.110	.006	18.88	1.117	.000
Time of Day	.011	.001	16.35	1.011	.000
Weather	.050	.007	6.66	1.051	.000
Crowdedness	.000	.001	-0.37	1.000	.712
Type of Appeal	.399	.002	169.92	1.491	.000
Promotional Signal	.581	.014	41.15	1.788	.000
Selection Correction	-.473	.011	-44.20	0.623	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,492,472.30				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.
We also updated the first-stage regression for shoppers' self-selection by including number of unique SKUs instead of number of items.

Table J4: Results with Number of Product Categories

	Model 13				
	β	SE	z	OR	p
Hypotheses					
H_1: Exposed to Digital Signage	.144	.004	35.26	1.155	.000
Controls					
Wear-out Campaign	-.079	.001	-83.40	0.924	.000
Learning Effect	.116	.001	114.71	1.123	.000
Temperature	.105	.007	14.54	1.111	.000
Rain	.071	.009	7.62	1.073	.000
Creativity	-.381	.002	-152.36	0.683	.000
Human Presence	-.087	.007	-12.22	0.916	.000
Exposed to Different Ads	-.060	.002	-27.36	0.942	.000
Number of Product Categories	.047	.000	124.66	1.048	.000
Total Spending	.178	.008	22.98	1.195	.000
Type of Product	-.021	.007	-3.03	0.979	.002
Brand Popularity	.294	.003	99.38	1.342	.000
New Product	1.703	.008	221.42	5.492	.000
Price of Product	-.428	.004	-113.46	0.652	.000
Price Cut	.368	.006	63.04	1.444	.000
Day of Week	.123	.006	21.08	1.131	.000
Time of Day	.012	.001	16.92	1.012	.000
Weather	.049	.007	6.49	1.050	.000
Crowdedness	-.013	.001	-10.12	0.987	.000
Type of Appeal	.403	.002	170.79	1.496	.000
Promotional Signal	.570	.014	40.18	1.768	.000
Selection Correction	-.284	.011	-26.70	0.753	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,493,192.80				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.
We also updated the first-stage regression for shoppers' self-selection by including number of product categories instead of number of items.

Table J5: Results with Number of Sectors

	Model 14				
	β	SE	z	OR	p
Hypotheses					
H_1: Exposed to Digital Signage	.147	.004	36.09	1.159	.000
Controls					
Wear-out Campaign	-.079	.001	-83.54	0.924	.000
Learning Effect	.117	.001	115.54	1.124	.000
Temperature	.107	.007	14.90	1.113	.000
Rain	.068	.009	7.29	1.070	.000
Creativity	-.382	.003	-152.53	0.683	.000
Human Presence	-.089	.007	-12.39	0.915	.000
Exposed to Different Ads	-.061	.002	-28.02	0.941	.000
Number of Sectors	.081	.001	116.05	1.084	.000
Total Spending	.194	.008	25.26	1.214	.000
Type of Product	-.014	.007	-2.06	0.986	.039
Brand Popularity	.291	.003	98.47	1.338	.000
New Product	1.701	.008	221.16	5.481	.000
Price of Product	-.429	.004	-113.44	0.651	.000
Price Cut	.367	.006	62.93	1.443	.000
Day of Week	.124	.006	21.22	1.132	.000
Time of Day	.011	.001	16.34	1.011	.000
Weather	.049	.007	6.55	1.050	.000
Crowdedness	-.016	.001	-11.88	0.984	.000
Type of Appeal	.404	.002	171.06	1.497	.000
Promotional Signal	.570	.014	40.21	1.768	.000
Selection Correction	-.226	.011	-21.27	0.798	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,493,973.60				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.
We also updated the first-stage regression for shoppers' self-selection by including number of sectors instead of number of items.

Table J6: Results with Shoppers that belong to Exposed and Control Groups

	Model 15				
	β	**SE**	**z**	**OR**	**p**
Hypotheses					
H_1: Exposed to Digital Signage	.090	.005	18.78	1.094	.000
Controls					
Wear-out Campaign	-.099	.001	-72.14	0.906	.000
Learning Effect	.009	.003	3.31	1.009	.001
Temperature	.090	.012	7.25	1.095	.000
Rain	-.023	.016	-1.44	0.978	.151
Creativity	-.364	.005	-77.70	0.695	.000
Human Presence	.085	.011	7.89	1.089	.000
Exposed to Different Ads	-.136	.004	-34.83	0.873	.000
Number of Items	2.332	.015	152.26	10.296	.000
Total Spending	.240	.011	22.87	1.271	.000
Type of Product	.090	.011	7.98	1.094	.000
Brand Popularity	.268	.005	51.70	1.307	.000
New Product	1.631	.012	136.84	5.111	.000
Price of Product	-.452	.007	-61.17	0.637	.000
Price Cut	.313	.009	35.06	1.368	.000
Day of Week	.145	.009	16.48	1.156	.000
Time of Day	.029	.001	28.42	1.029	.000
Weather	.021	.011	1.91	1.021	.056
Crowdedness	-.010	.002	-4.39	0.990	.000
Type of Appeal	.371	.004	97.70	1.450	.000
Promotional Signal	1.045	.021	50.08	2.843	.000
Selection Correction	-.065	.029	-2.24	0.937	.025
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-678,139.57				
N	9,373,297				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table J7: Results with Weekly Fixed-Effects

	Model 16				
	β	**SE**	**z**	**OR**	**p**
Hypotheses					
H_1: Exposed to Digital Signage	.077	.004	18.65	1.080	.000
Controls					
Wear-out Campaign	-.082	.001	-82.47	0.921	.000
Learning Effect	.111	.001	106.96	1.117	.000
Temperature	.166	.008	21.46	1.181	.000
Rain	.058	.010	5.97	1.060	.000
Creativity	-.393	.003	-150.68	0.675	.000
Human Presence	-.142	.008	-18.68	0.868	.000
Exposed to Different Ads	-.067	.002	-28.85	0.935	.000
Number of Items	2.109	.008	261.19	8.237	.000
Total Spending	.191	.007	28.70	1.210	.000
Type of Product	-.010	.007	-1.34	0.990	.181
Brand Popularity	.297	.003	99.77	1.346	.000
New Product	1.730	.008	218.25	5.643	.000
Price of Product	-.444	.004	-109.80	0.642	.000
Price Cut	.380	.006	62.54	1.462	.000
Day of Week	.132	.006	22.38	1.141	.000
Time of Day	.008	.001	12.40	1.008	.000
Weather	.078	.008	9.86	1.081	.000
Crowdedness	-.018	.001	-13.60	0.982	.000
Type of Appeal	.431	.003	169.75	1.539	.000
Promotional Signal	.551	.015	37.88	1.736	.000
Selection Correction	-.171	.011	-15.28	0.843	.000
Fixed Effects					
Store	included				
Week	included				
Log-likelihood	-1,453,434.20				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table J8: Results with Product Category Fixed-Effects

	Model 17				
	β	SE	z	OR	p
Hypotheses					
H_1: Exposed to Digital Signage	.124	.004	30.05	1.132	.000
Controls					
Wear-out Campaign	-.060	.001	-52.09	0.941	.000
Learning Effect	.127	.002	66.30	1.136	.000
Temperature	.088	.007	12.25	1.092	.000
Rain	.073	.010	7.26	1.076	.000
Creativity	-.487	.004	-112.51	0.614	.000
Human Presence	-.758	.015	-50.11	0.469	.000
Exposed to Different Ads	-.030	.002	-12.78	0.971	.000
Number of Items	2.050	.009	235.59	7.769	.000
Total Spending	.189	.007	27.41	1.208	.000
Type of Product	-.885	.011	-79.87	0.413	.000
Brand Popularity	.692	.009	73.45	1.998	.000
New Product	2.936	.026	113.53	18.835	.000
Price of Product	-.511	.008	-66.58	0.600	.000
Price Cut	.359	.006	59.63	1.432	.000
Day of Week	.108	.006	18.53	1.114	.000
Time of Day	.010	.001	14.87	1.010	.000
Weather	.051	.007	6.82	1.052	.000
Crowdedness	.001	.001	0.86	1.001	.390
Type of Appeal	.366	.006	64.57	1.442	.000
Promotional Signal	.508	.017	30.64	1.662	.000
Selection Correction	-.368	.013	-27.91	0.692	.000
Fixed Effects					
Store	included				
Month	included				
Product Category	included				
Log-likelihood	-1,434,489.10				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Web Appendix K. Additional Interaction Effects

Table K1: Day of Week Interaction Effects

	Model 18				
	β	SE	z	OR	p
Day of Week Effects					
Exposed to Digital Signage	.064	.011	5.73	1.066	.000
Tuesday × Exposed	.054	.015	3.54	1.056	.000
Wednesday × Exposed	.014	.015	0.90	1.014	.368
Thursday × Exposed	-.020	.014	-1.41	0.980	.159
Friday × Exposed	-.001	.014	-0.07	0.999	.947
Saturday × Exposed	.042	.014	3.01	1.043	.003
Controls					
Wear-out Campaign	-.081	.001	-84.73	0.922	.000
Learning Effect	.114	.001	111.89	1.121	.000
Temperature	.093	.007	12.82	1.097	.000
Rain	.043	.010	4.46	1.044	.000
Creativity	-.396	.003	-153.96	0.673	.000
Human Presence	-.134	.007	-18.59	0.875	.000
Exposed to Different Ads	-.062	.002	-28.20	0.940	.000
Number of Items	2.107	.008	262.52	8.227	.000
Total Spending	.190	.007	28.47	1.209	.000
Type of Product	-.008	.007	-1.16	0.992	.246
Brand Popularity	.287	.003	97.01	1.332	.000
New Product	1.732	.008	221.91	5.651	.000
Price of Product	-.436	.004	-112.77	0.646	.000
Price Cut	.383	.006	65.11	1.466	.000
Tuesday	.106	.012	8.63	1.112	.000
Wednesday	.161	.012	13.30	1.175	.000
Thursday	.182	.011	16.09	1.199	.000
Friday	.301	.011	27.01	1.351	.000
Saturday	.268	.011	24.02	1.308	.000
Time of Day	.008	.001	11.19	1.008	.000
Weather	.096	.008	12.76	1.101	.000
Crowdedness	-.023	.001	-16.87	0.978	.000
Type of Appeal	.422	.002	175.29	1.525	.000
Promotional Signal	.555	.014	38.55	1.742	.000
Selection Correction	-.142	.011	-13.02	0.867	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,454,461.00				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors. Monday is the base category for day of the week.

Table K2: Time of Day Interaction Effects

	Model 19				
	β	SE	z	OR	p
Time of Day Effects					
Exposed to Digital Signage	.273	.041	6.60	1.314	.000
9am × Exposed	-.226	.048	-4.67	0.798	.000
10am × Exposed	-.285	.045	-6.40	0.752	.000
11am × Exposed	-.307	.044	-7.05	0.735	.000
12am × Exposed	-.327	.043	-7.55	0.721	.000
1pm × Exposed	-.280	.043	-6.47	0.756	.000
2pm × Exposed	-.219	.043	-5.05	0.803	.000
3pm × Exposed	-.200	.044	-4.59	0.819	.000
4pm × Exposed	-.142	.044	-3.26	0.867	.001
5pm × Exposed	-.147	.043	-3.38	0.863	.001
6pm × Exposed	-.113	.043	-2.60	0.893	.009
7pm × Exposed	-.109	.044	-2.51	0.897	.012
8pm × Exposed	-.098	.044	-2.22	0.907	.027
9pm × Exposed	-.119	.045	-2.63	0.888	.008
10pm × Exposed	-.080	.049	-1.63	0.923	.103
11pm × Exposed	-.134	.058	-2.29	0.874	.022
Controls					
Wear-out Campaign	-.081	.001	-84.52	0.922	.000
Learning Effect	.114	.001	111.50	1.121	.000
Temperature	.105	.007	14.58	1.111	.000
Rain	.038	.010	3.92	1.038	.000
Creativity	-.393	.003	-152.58	0.675	.000
Human Presence	-.129	.007	-17.81	0.879	.000
Exposed to Different Ads	-.064	.002	-28.36	0.938	.000
Number of Items	2.118	.008	259.62	8.312	.000
Total Spending	.189	.007	28.07	1.207	.000
Type of Product	-.008	.007	-1.06	0.992	.288
Brand Popularity	.288	.003	96.94	1.333	.000
New Product	1.732	.008	221.67	5.652	.000
Price of Product	-.436	.004	-112.74	0.647	.000
Price Cut	.377	.006	64.21	1.458	.000
Day of Week	.119	.006	20.22	1.127	.000
9 am	.254	.040	6.31	1.289	.000
10 am	.373	.038	9.91	1.452	.000
11 am	.421	.037	11.37	1.524	.000
12 am	.454	.037	12.27	1.575	.000
1 pm	.433	.037	11.70	1.543	.000
2 pm	.385	.037	10.37	1.470	.000
3 pm	.346	.037	9.28	1.413	.000
4 pm	.312	.037	8.36	1.367	.000
5 pm	.343	.037	9.21	1.409	.000
6 pm	.348	.037	9.35	1.417	.000
7 pm	.364	.037	9.75	1.439	.000
8 pm	.364	.038	9.67	1.439	.000
9 pm	.387	.038	10.06	1.473	.000
10 pm	.354	.041	8.55	1.425	.000
11 pm	.452	.049	9.30	1.572	.000
Weather	.070	.007	9.44	1.073	.000
Crowdedness	-.019	.001	-13.06	0.981	.000
Type of Appeal	.421	.002	174.59	1.524	.000
Promotional Signal	.557	.014	38.63	1.746	.000
Selection Correction	-.151	.012	-13.06	0.860	.000
Fixed Effects					
Store			included		
Month			included		
Log-likelihood			-1,455,090.20		
N			29,999,084		

Notes: β = unstandardized coefficients, SE = robust standard errors. 8am is the base category for time of the day.

Table K3: Product Type–Day of Week Interaction Effects

	Model 20				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type x Weekend × Exposed	-.017	.018	-0.96	0.983	.338
Product Type × Weekend	.061	.015	3.98	1.063	.000
Hypotheses					
H_1: Exposed to Digital Signage	.050	.009	5.39	1.051	.000
H_2: Type of Product × Exposed	.134	.012	11.44	1.143	.000
H_3: Brand Popularity × Exposed	.024	.005	4.80	1.024	.000
H_4: Product Novelty × Exposed	.188	.012	15.32	1.206	.000
H_5: Price of Product × Exposed	-.050	.007	-7.25	0.951	.000
H_6: Price Cut × Exposed	-.007	.010	-0.70	0.993	.487
H_7: Day of Week × Exposed	.040	.010	3.98	1.040	.000
H_8: Time of Day × Exposed	.025	.001	22.00	1.025	.000
H_9: Weather × Exposed	.059	.012	5.03	1.060	.000
H_{10}: Crowdedness × Exposed	.011	.001	7.23	1.011	.000
H_{11}: Type of Appeal × Exposed	.012	.003	3.55	1.012	.000
H_{12}: Promotional Signal × Exposed	-.099	.023	-4.41	0.906	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.025	.002	-14.62	0.975	.000
Learning Effect × Exposed	.034	.002	19.49	1.034	.000
Temperature × Exposed	.014	.008	1.69	1.014	.090
Rain × Exposed	-.056	.016	-3.56	0.945	.000
Creativity × Exposed	.002	.004	0.57	1.002	.568
Human Presence × Exposed	-.111	.011	-10.30	0.895	.000
Controls					
Wear-out Campaign	-.067	.001	-50.14	0.935	.000
Learning Effect	.099	.001	77.46	1.104	.000
Temperature	.094	.008	11.38	1.098	.000
Rain	.076	.013	5.62	1.079	.000
Creativity	-.399	.004	-113.61	0.671	.000
Human Presence	-.075	.010	-7.83	0.928	.000
Exposed to Different Ads	-.066	.002	-29.26	0.936	.000
Number of Items	2.101	.008	260.31	8.177	.000
Total Spending	.187	.007	27.45	1.205	.000
Type of Product	-.080	.010	-7.81	0.924	.000
Brand Popularity	.276	.004	66.21	1.318	.000
New Product	1.647	.011	154.16	5.192	.000
Price of Product	-.418	.005	-84.32	0.658	.000
Price Cut	.382	.008	48.37	1.465	.000
Day of Week	.103	.008	12.89	1.109	.000
Time of Day	-.005	.001	-5.50	0.995	.000
Weather	.035	.010	3.62	1.035	.000
Crowdedness	-.020	.001	-13.45	0.980	.000
Type of Appeal	.409	.003	135.28	1.505	.000
Promotional Signal	.590	.019	30.30	1.804	.000
Selection Correction	-.206	.011	-18.21	0.814	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,454,408.30				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table K4: Product Type–Time of Day Interaction Effects

	Model 21				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type × Time of Day × Exposed	-.007	.002	-3.47	0.993	.001
Product Type × Time of Day	.019	.002	11.20	1.019	.000
Hypotheses					
H_1: Exposed to Digital Signage	.050	.009	5.34	1.051	.000
H_2: Type of Product × Exposed	.119	.011	10.59	1.127	.000
H_3: Brand Popularity × Exposed	.026	.005	5.19	1.027	.000
H_4: Product Novelty × Exposed	.182	.012	14.79	1.200	.000
H_5: Price of Product × Exposed	-.049	.007	-7.17	0.952	.000
H_6: Price Cut × Exposed	-.006	.010	-0.65	0.994	.516
H_7: Day of Week × Exposed	.042	.010	4.39	1.043	.000
H_8: Time of Day × Exposed	.024	.001	20.18	1.024	.000
H_9: Weather × Exposed	.058	.012	4.98	1.059	.000
H_{10}: Crowdedness × Exposed	.011	.001	7.32	1.011	.000
H_{11}: Type of Appeal × Exposed	.011	.003	3.14	1.011	.002
H_{12}: Promotional Signal × Exposed	-.104	.023	-4.59	0.902	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.025	.002	-14.52	0.975	.000
Learning Effect × Exposed	.033	.002	19.24	1.034	.000
Temperature × Exposed	.013	.008	1.57	1.013	.117
Rain × Exposed	-.057	.016	-3.58	0.945	.000
Creativity × Exposed	.002	.004	0.51	1.002	.608
Human Presence × Exposed	-.111	.011	-10.31	0.894	.000
Controls					
Wear-out Campaign	-.067	.001	-50.26	0.935	.000
Learning Effect	.100	.001	77.88	1.105	.000
Temperature	.096	.008	11.68	1.101	.000
Rain	.075	.013	5.57	1.078	.000
Creativity	-.401	.004	-114.18	0.669	.000
Human Presence	-.078	.010	-8.22	0.925	.000
Exposed to Different Ads	-.066	.002	-29.07	0.937	.000
Number of Items	2.105	.008	260.85	8.209	.000
Total Spending	.187	.007	27.50	1.205	.000
Type of Product	-.051	.010	-5.17	0.950	.000
Brand Popularity	.271	.004	64.72	1.311	.000
New Product	1.660	.011	154.21	5.260	.000
Price of Product	-.420	.005	-84.67	0.657	.000
Price Cut	.381	.008	48.19	1.464	.000
Day of Week	.095	.008	12.25	1.099	.000
Time of Day	-.002	.001	-1.97	0.998	.049
Weather	.038	.010	3.98	1.039	.000
Crowdedness	-.021	.001	-14.28	0.979	.000
Type of Appeal	.413	.003	135.33	1.511	.000
Promotional Signal	.599	.019	30.78	1.821	.000
Selection Correction	-.195	.011	-17.18	0.823	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,454,289.70				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table K5: Product Type–Type of Appeal Interaction Effects

	Model 22				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type × Type of Appeal × Exposed	-.033	.008	-4.12	0.967	.000
Product Type × Type of Appeal	-.457	.007	-68.10	0.633	.000
Hypotheses					
H_1: Exposed to Digital Signage	.043	.010	4.45	1.044	.000
H_2: Type of Product × Exposed	.086	.014	6.08	1.090	.000
H_3: Brand Popularity × Exposed	.016	.005	3.03	1.016	.002
H_4: Product Novelty × Exposed	.064	.013	5.00	1.066	.000
H_5: Price of Product × Exposed	-.060	.008	-7.29	0.942	.000
H_6: Price Cut × Exposed	.026	.010	2.67	1.027	.008
H_7: Day of Week × Exposed	.037	.010	3.87	1.038	.000
H_8: Time of Day × Exposed	.024	.001	21.46	1.025	.000
H_9: Weather × Exposed	.031	.012	2.69	1.032	.007
H_{10}: Crowdedness × Exposed	.011	.002	7.22	1.011	.000
H_{11}: Type of Appeal × Exposed	-.022	.004	-5.56	0.978	.000
H_{12}: Promotional Signal × Exposed	-.104	.022	-4.61	0.902	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.018	.002	-10.27	0.982	.000
Learning Effect × Exposed	.037	.002	19.48	1.038	.000
Temperature × Exposed	.029	.009	3.31	1.030	.001
Rain × Exposed	-.065	.016	-4.02	0.937	.000
Creativity × Exposed	.022	.005	4.77	1.022	.000
Human Presence × Exposed	-.083	.011	-7.29	0.920	.000
Controls					
Wear-out Campaign	-.069	.001	-50.22	0.933	.000
Learning Effect	.121	.001	87.95	1.129	.000
Temperature	.072	.008	8.62	1.075	.000
Rain	.082	.014	6.02	1.086	.000
Creativity	-.302	.004	-81.26	0.739	.000
Human Presence	-.079	.010	-8.02	0.924	.000
Exposed to Different Ads	-.066	.002	-28.84	0.936	.000
Number of Items	2.109	.008	257.62	8.237	.000
Total Spending	.188	.007	27.65	1.207	.000
Type of Product	.113	.012	9.36	1.120	.000
Brand Popularity	.359	.004	81.96	1.432	.000
New Product	1.462	.011	137.26	4.315	.000
Price of Product	-.450	.006	-76.23	0.637	.000
Price Cut	.393	.008	49.72	1.482	.000
Day of Week	.074	.008	9.53	1.076	.000
Time of Day	-.006	.001	-6.63	0.994	.000
Weather	.006	.010	0.66	1.006	.510
Crowdedness	-.011	.001	-7.17	0.989	.000
Type of Appeal	.306	.003	94.82	1.358	.000
Promotional Signal	.409	.019	21.11	1.505	.000
Selection Correction	-.189	.012	-16.26	0.828	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,445,944.50				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors

Table K6: Product Type–Weather Interaction Effects

	Model 23				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type × Weather × Exposed	.071	.020	3.52	1.073	.000
Product Type × Weather	-.068	.017	-3.98	0.934	.000
Hypotheses					
H_1: Exposed to Digital Signage	.051	.009	5.47	1.052	.000
H_2: Type of Product × Exposed	.136	.011	12.07	1.145	.000
H_3: Brand Popularity × Exposed	.023	.005	4.56	1.023	.000
H_4: Product Novelty × Exposed	.191	.012	15.53	1.211	.000
H_5: Price of Product × Exposed	-.050	.007	-7.28	0.951	.000
H_6: Price Cut × Exposed	-.006	.010	-0.62	0.994	.536
H_7: Day of Week × Exposed	.040	.010	4.14	1.041	.000
H_8: Time of Day × Exposed	.025	.001	21.97	1.025	.000
H_9: Weather × Exposed	.072	.012	5.91	1.074	.000
H_{10}: Crowdedness × Exposed	.011	.001	7.08	1.011	.000
H_{11}: Type of Appeal × Exposed	.013	.003	3.80	1.013	.000
H_{12}: Promotional Signal × Exposed	-.104	.022	-4.64	0.901	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.025	.002	-14.63	0.975	.000
Learning Effect × Exposed	.034	.002	19.56	1.034	.000
Temperature × Exposed	.015	.008	1.74	1.015	.081
Rain × Exposed	-.056	.016	-3.54	0.946	.000
Creativity × Exposed	.001	.004	0.29	1.001	.775
Human Presence × Exposed	-.112	.011	-10.34	0.894	.000
Controls					
Wear-out Campaign	-.067	.001	-50.16	0.935	.000
Learning Effect	.099	.001	77.09	1.104	.000
Temperature	.096	.008	11.67	1.101	.000
Rain	.075	.013	5.58	1.078	.000
Creativity	-.398	.004	-112.64	0.672	.000
Human Presence	-.075	.010	-7.86	0.928	.000
Exposed to Different Ads	-.065	.002	-28.86	0.937	.000
Number of Items	2.100	.008	260.17	8.168	.000
Total Spending	.187	.007	27.42	1.205	.000
Type of Product	-.074	.010	-7.50	0.928	.000
Brand Popularity	.278	.004	66.39	1.320	.000
New Product	1.642	.011	152.65	5.167	.000
Price of Product	-.418	.005	-84.02	0.659	.000
Price Cut	.382	.008	48.36	1.465	.000
Day of Week	.096	.008	12.40	1.101	.000
Time of Day	-.005	.001	-5.47	0.995	.000
Weather	.025	.010	2.47	1.025	.013
Crowdedness	-.020	.001	-13.51	0.980	.000
Type of Appeal	.408	.003	134.22	1.503	.000
Promotional Signal	.594	.019	30.47	1.811	.000
Selection Correction	-.208	.011	-18.38	0.812	.000
Fixed Effects					
Store			included		
Month			included		
Log-likelihood			-1,454,416.60		
N			29,999,084		

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table K7: Product Type–Rain Interaction Effects

	Model 24				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type × Rain × Exposed	-.016	.036	-0.43	0.984	.665
Product Type × Rain	.410	.030	13.67	1.507	.000
Hypotheses					
H_1: Exposed to Digital Signage	.049	.009	5.22	1.050	.000
H_2: Type of Product × Exposed	.133	.011	11.92	1.142	.000
H_3: Brand Popularity × Exposed	.024	.005	4.67	1.024	.000
H_4: Product Novelty × Exposed	.188	.012	15.37	1.207	.000
H_5: Price of Product × Exposed	-.051	.007	-7.35	0.951	.000
H_6: Price Cut × Exposed	-.004	.010	-0.40	0.996	.692
H_7: Day of Week × Exposed	.042	.010	4.35	1.043	.000
H_8: Time of Day × Exposed	.025	.001	21.89	1.025	.000
H_9: Weather × Exposed	.057	.012	4.88	1.058	.000
H_{10}: Crowdedness × Exposed	.010	.001	6.90	1.010	.000
H_{11}: Type of Appeal × Exposed	.012	.003	3.64	1.012	.000
H_{12}: Promotional Signal × Exposed	-.100	.022	-4.45	0.905	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.025	.002	-14.45	0.975	.000
Learning Effect × Exposed	.034	.002	19.52	1.034	.000
Temperature × Exposed	.014	.008	1.63	1.014	.103
Rain × Exposed	-.055	.016	-3.40	0.946	.001
Creativity × Exposed	.002	.004	0.53	1.002	.596
Human Presence × Exposed	-.111	.011	-10.25	0.895	.000
Controls					
Wear-out Campaign	-.067	.001	-50.22	0.935	.000
Learning Effect	.100	.001	78.11	1.105	.000
Temperature	.094	.008	11.38	1.098	.000
Rain	.071	.014	5.10	1.073	.000
Creativity	-.397	.004	-112.66	0.673	.000
Human Presence	-.071	.010	-7.48	0.931	.000
Exposed to Different Ads	-.064	.002	-28.58	0.938	.000
Number of Items	2.102	.008	260.25	8.179	.000
Total Spending	.187	.007	27.53	1.206	.000
Type of Product	-.078	.010	-7.92	0.925	.000
Brand Popularity	.281	.004	67.11	1.324	.000
New Product	1.634	.011	153.23	5.122	.000
Price of Product	-.418	.005	-83.82	0.659	.000
Price Cut	.380	.008	48.08	1.462	.000
Day of Week	.091	.008	11.75	1.095	.000
Time of Day	-.005	.001	-5.51	0.995	.000
Weather	.032	.010	3.37	1.033	.001
Crowdedness	-.019	.001	-13.12	0.981	.000
Type of Appeal	.405	.003	134.27	1.500	.000
Promotional Signal	.583	.019	30.02	1.791	.000
Selection Correction	-.209	.011	-18.45	0.811	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,454,088.90				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Table K8: Product Type–Temperature Interaction Effects

	Model 25				
	β	SE	z	OR	p
Three-way Interaction effects					
Product Type × Temperature × Exposed	-.150	.016	-9.08	0.861	.000
Product Type × Temperature	-.691	.014	-50.77	0.501	.000
Hypotheses					
H_1: Exposed to Digital Signage	.056	.010	5.73	1.058	.000
H_2: Type of Product × Exposed	.071	.013	5.68	1.074	.000
H_3: Brand Popularity × Exposed	.050	.005	9.22	1.052	.000
H_4: Product Novelty × Exposed	.153	.013	11.96	1.165	.000
H_5: Price of Product × Exposed	-.042	.007	-5.92	0.959	.000
H_6: Price Cut × Exposed	-.015	.010	-1.49	0.985	.136
H_7: Day of Week × Exposed	.049	.010	5.09	1.050	.000
H_8: Time of Day × Exposed	.025	.001	22.63	1.026	.000
H_9: Weather × Exposed	.062	.012	5.36	1.064	.000
H_{10}: Crowdedness × Exposed	.011	.001	7.65	1.011	.000
H_{11}: Type of Appeal × Exposed	.007	.003	1.90	1.007	.057
H_{12}: Promotional Signal × Exposed	-.095	.022	-4.24	0.910	.000
Additional Interactions					
Wear-out Campaign × Exposed	-.016	.002	-8.86	0.985	.000
Learning Effect × Exposed	.026	.002	14.93	1.026	.000
Temperature × Exposed	-.004	.009	-0.45	0.996	.652
Rain × Exposed	-.059	.016	-3.69	0.943	.000
Creativity × Exposed	.019	.004	4.46	1.019	.000
Human Presence × Exposed	-.102	.011	-8.87	0.903	.000
Controls					
Wear-out Campaign	-.068	.001	-49.68	0.934	.000
Learning Effect	.090	.001	70.40	1.095	.000
Temperature	.011	.008	1.25	1.011	.210
Rain	.098	.014	7.25	1.103	.000
Creativity	-.376	.004	-105.99	0.687	.000
Human Presence	.019	.010	1.93	1.019	.054
Exposed to Different Ads	-.062	.002	-27.93	0.940	.000
Number of Items	2.086	.008	257.97	8.054	.000
Total Spending	.184	.007	26.88	1.202	.000
Type of Product	-.246	.011	-23.28	0.782	.000
Brand Popularity	.348	.004	78.20	1.416	.000
New Product	1.523	.011	139.02	4.585	.000
Price of Product	-.410	.005	-80.57	0.664	.000
Price Cut	.377	.008	47.75	1.457	.000
Day of Week	.110	.008	14.17	1.116	.000
Time of Day	-.005	.001	-5.12	0.995	.000
Weather	.035	.010	3.62	1.035	.000
Crowdedness	-.019	.001	-12.89	0.981	.000
Type of Appeal	.364	.003	117.86	1.439	.000
Promotional Signal	.602	.019	31.27	1.825	.000
Selection Correction	-.242	.011	-21.36	0.785	.000
Fixed Effects					
Store	included				
Month	included				
Log-likelihood	-1,449,612.40				
N	29,999,084				

Notes: β = unstandardized coefficients, SE = robust standard errors.

Web Appendix L. Probit Models for the Main Analysis

	Model 26				Model 27			
	β	SE	z	p	β	SE	z	p
Hypotheses								
H_1: Exposed to Digital Signage	.032	.002	19.15	.000	.016	.003	4.68	.000
H_2: Type of Product × Exposed					.061	.005	13.50	.000
H_3: Brand Popularity × Exposed					.025	.002	12.68	.000
H_4: Product Novelty × Exposed					.123	.005	24.24	.000
H_5: Price of Product × Exposed					-.026	.003	-9.47	.000
H_6: Price Cut × Exposed					.006	.004	1.53	.126
H_7: Day of Week × Exposed					.015	.004	3.96	.000
H_8: Time of Day × Exposed					.011	.000	24.12	.000
H_9: Weather × Exposed					.027	.005	5.65	.000
H_{10}: Crowdedness × Exposed					.005	.001	7.77	.000
H_{11}: Type of Appeal × Exposed					.010	.001	7.03	.000
H_{12}: Promotional Signal × Exposed					-.033	.009	-3.72	.000
Additional Interactions								
Wear-out Campaign × Exposed					-.009	.001	-13.53	.000
Learning Effect × Exposed					.013	.001	19.22	.000
Temperature × Exposed					.006	.003	1.75	.080
Rain × Exposed					-.021	.006	-3.36	.001
Creativity × Exposed					-.005	.002	-3.36	.001
Human Presence × Exposed					-.035	.004	-8.41	.000
Controls								
Wear-out Campaign	-.033	.000	-86.34	.000	-.028	.001	-53.08	.000
Learning Effect	.042	.000	113.36	.000	.037	.000	79.96	.000
Temperature	.040	.003	14.21	.000	.036	.003	11.40	.000
Rain	.014	.004	3.60	.000	.027	.005	5.20	.000
Creativity	-.157	.001	-156.72	.000	-.157	.001	-120.71	.000
Human Presence	-.021	.003	-7.51	.000	-.008	.004	-2.14	.033
Exposed to Different Ads	-.015	.001	-18.53	.000	-.015	.001	-18.41	.000
Number of Items	.917	.003	262.42	.000	.915	.004	260.40	.000
Total Spending	.093	.003	33.28	.000	.092	.003	32.73	.000
Type of Product	-.032	.003	-11.90	.000	-.060	.004	-15.76	.000
Brand Popularity	.110	.001	95.95	.000	.096	.002	59.81	.000
New Product	.665	.003	214.97	.000	.605	.004	141.34	.000
Price of Product	-.131	.001	-97.19	.000	-.121	.002	-73.14	.000
Price Cut	.156	.002	66.15	.000	.153	.003	48.81	.000
Day of Week	.042	.002	17.99	.000	.035	.003	11.45	.000
Time of Day	.003	.000	11.54	.000	-.003	.000	-7.43	.000
Weather	.027	.003	9.06	.000	.012	.004	3.22	.001
Crowdedness	-.007	.001	-13.44	.000	-.009	.001	-15.23	.000
Type of Appeal	.159	.001	174.65	.000	.151	.001	130.43	.000
Promotional Signal	.228	.006	41.40	.000	.234	.007	31.72	.000
Selection Correction	-.095	.004	-22.86	.000	-.105	.004	-24.22	.000
Fixed Effects								
Store		included				included		
Month		included				included		
Log-likelihood		-1,463,283.20				-1,461,819.40		
N		29,999,084				29,999,084		

Notes: OR = odds ratios, SE = robust standard errors.

Web Appendix M. Placement of Digital Signage

Does the placement of digital signage relative to the product influence its effectiveness? Surprisingly, Nanni and Ordanini (2024) indicate that digital signage works well for products outside the department in which the screens are located. The ads in our study are randomly played on all screens regardless of their location, and hence their placement should not affect the observed results. Nevertheless, intrigued by the counterintuitive finding, we collected data on the placement of digital signage relative to the featured products for 183 campaigns, a total of 23,523,924 shoppers with shopping carts. Due to a database change of the cooperating company, we were not able to retrieve this information for all campaigns in our sample.

Digital signage was installed in ten stores, each with five screens. For every exposed shopper, we retrieved the screen for each campaign (the same shopper may be exposed to multiple screens and campaigns). Using detailed blueprints of all 10 stores which contain the placements of all 5 screens and all 15 product categories used in the campaigns, we calculated the resulting 750 distances between the screen location and the midpoint of the product category measured in meters. Neither the screen locations nor the product category locations changed during our data collection, and while the store managers have a certain placement discretion within the product category, they are not allowed to change the strategic placement of the product category.

Given that the same shopper may be exposed to the same campaign on multiple screens we use two different measures for the distance to the screen for multiple exposures: minimum distance and mean distance, which are highly correlated ($p = .89$, $p < .001$) as expected given that values are identical for those shoppers that were only exposed once to the campaign. All results from the main analyses hold for this sub-sample, as displayed in Tables M1 and M2.

We find a negative interaction effect between distance to the screen and exposure both in the logit specification reported in Table M1 (minimum distance: $\beta = -.002$, $p < .001$; mean distance: $\beta = -.002$, $p < .001$). The average distance of the product from the screen is 30 meters (98.4 feet), and the odds ratios of the logit model indicate that for every 10 meters (32.8 feet) the product is closer (away) from the screen, the effect of exposure increases (decreases) by 2%. Importantly, none of the other interaction effects are affected by including distance to screen, indicating that the randomization of screens worked and robustness of our main findings regarding the placement of digital signage.

Table M1. Results for the Main Effect in the Placement Sample

	Model 28: Main Analyses				Model 29: Distance as Minimum				Model 30: Distance as Mean			
	β	**SE**	**z**	**p**	**β**	**SE**	**z**	**p**	**β**	**SE**	**z**	**p**
Distance to Screen												
Distance to Screen × Exposed					-.002	.000	-11.33	.000	-.002	.000	-9.55	.000
Hypotheses												
H_1: Exposed to Digital Signage	.025	.005	5.31	.000	.057	.005	10.46	.000	.056	.006	9.72	.000
Controls												
Wear-out Campaign	-.088	.001	-72.34	.000	-.088	.001	-72.20	.000	-.088	.001	-72.24	.000
Learning Effect	.155	.002	98.47	.000	.155	.002	98.22	.000	.155	.002	98.39	.000
Temperature	.103	.008	12.89	.000	.103	.008	12.91	.000	.103	.008	12.88	.000
Rain	-.015	.013	-1.21	.227	-.016	.013	-1.25	.213	-.016	.013	-1.30	.192
Creativity	-.619	.005	-120.66	.000	-.618	.005	-120.30	.000	-.618	.005	-120.28	.000
Human Presence	-.456	.010	-47.56	.000	-.454	.010	-47.42	.000	-.454	.010	-47.41	.000
Exposed to Different Ads	.089	.003	32.35	.000	.092	.003	33.20	.000	.090	.003	32.50	.000
Number of Items	2.344	.010	238.35	.000	2.342	.010	238.10	.000	2.343	.010	238.23	.000
Total Spending	.199	.008	25.50	.000	.200	.008	25.51	.000	.200	.008	25.50	.000
Type of Product	.420	.015	28.76	.000	.418	.015	28.57	.000	.417	.015	28.51	.000
Brand Popularity	.132	.004	32.53	.000	.132	.004	32.57	.000	.132	.004	32.58	.000
New Product	1.506	.012	130.04	.000	1.510	.012	130.18	.000	1.510	.012	130.11	.000
Price of Product	-.427	.005	-85.14	.000	-.427	.005	-85.20	.000	-.427	.005	-85.20	.000
Price Cut	.044	.007	6.26	.000	.044	.007	6.31	.000	.044	.007	6.30	.000
Day of Week	.145	.006	22.83	.000	.146	.006	22.88	.000	.145	.006	22.84	.000
Time of Day	-.002	.001	-2.20	.028	-.002	.001	-2.17	.030	-.002	.001	-2.19	.029
Weather	.032	.008	3.97	.000	.033	.008	3.99	.000	.033	.008	4.00	.000
Crowdedness	-.010	.001	-8.82	.000	-.010	.001	-9.00	.000	-.010	.001	-8.89	.000
Type of Appeal	.526	.004	146.44	.000	.525	.004	146.11	.000	.525	.004	146.03	.000
Promotional Signal	.445	.019	23.95	.000	.447	.019	24.03	.000	.446	.019	24.02	.000
Selection Correction	.423	.015	27.81	.000	.422	.015	27.72	.000	.424	.015	27.86	.000
Fixed Effects												
Store	included				included				included			
Month	included				included				included			
Log-likelihood	-1,116,396.20				-1,116,333.50				-1,116,352.20			
N	23,523,924				23,523,924				23,523,924			

Notes: β = unstandardized coefficients, SE = robust standard errors. We do not include a main effect of distance to the screen because we only have this information for exposed shoppers.

Table M2. Results for the Interaction Effects in the Placement Sample

	Model 31: Main Analyses				Model 32: Distance as Minimum				Model 33: Distance as Mean			
	β	SE	z	p	β	SE	z	p	β	SE	z	p
Distance to Screen												
Distance to Screen × Exposed					-.002	.000	-13.45	.000	-.002	.000	-10.37	.000
Hypotheses												
H_1: Exposed to Digital Signage	-.006	.014	-0.47	.639	.033	.014	2.35	.019	.029	.014	2.05	.040
H_2: Type of Product × Exposed	.009	.028	0.31	.759	-.001	.028	-0.03	.975	.002	.028	0.08	.936
H_3: Brand Popularity × Exposed	.041	.007	5.71	.000	.044	.007	6.14	.000	.043	.007	5.95	.000
H_4: Product Novelty × Exposed	.108	.022	4.87	.000	.124	.022	5.56	.000	.117	.022	5.26	.000
H_5: Price of Product × Exposed	-.032	.010	-3.18	.001	-.032	.010	-3.15	.002	-.032	.010	-3.13	.002
H_6: Price Cut × Exposed	.033	.012	2.73	.006	.036	.012	2.93	.003	.035	.012	2.84	.005
H_7: Day of Week × Exposed	.016	.011	1.48	.138	.014	.011	1.36	.175	.016	.011	1.50	.134
H_8: Time of Day × Exposed	.033	.001	26.11	.000	.034	.001	26.24	.000	.034	.001	26.16	.000
H_9: Weather × Exposed	.017	.013	1.33	.183	.019	.013	1.48	.138	.020	.013	1.49	.136
H_{10}: Crowdedness × Exposed	.032	.002	18.96	.000	.033	.002	19.38	.000	.032	.002	18.87	.000
H_{11}: Type of Appeal × Exposed	-.052	.007	-7.32	.000	-.053	.007	-7.44	.000	-.055	.007	-7.63	.000
H_{12}: Promotional Signal × Exposed	-.040	.035	-1.14	.255	-.044	.035	-1.24	.217	-.040	.035	-1.13	.259
Additional Interactions												
Wear-out Campaign × Exposed	-.018	.002	-8.21	.000	-.018	.002	-8.03	.000	-.018	.002	-8.12	.000
Learning Effect × Exposed	.058	.003	21.44	.000	.057	.003	21.01	.000	.057	.003	21.15	.000
Temperature × Exposed	-.075	.010	-7.26	.000	-.069	.010	-6.70	.000	-.070	.010	-6.81	.000
Rain × Exposed	-.008	.022	-0.36	.716	-.013	.022	-0.58	.561	-.011	.022	-0.49	.622
Creativity × Exposed	.094	.011	8.79	.000	.094	.011	8.76	.000	.095	.011	8.84	.000
Human Presence × Exposed	.156	.018	8.65	.000	.156	.018	8.63	.000	.157	.018	8.70	.000
Controls												
Wear-out Campaign	-.077	.002	-43.43	.000	-.077	.002	-43.50	.000	-.077	.002	-43.45	.000
Learning Effect	.128	.002	64.86	.000	.128	.002	64.88	.000	.128	.002	64.95	.000
Temperature	.141	.009	15.46	.000	.138	.009	15.17	.000	.138	.009	15.20	.000
Rain	-.017	.018	-0.93	.353	-.014	.018	-0.79	.430	-.016	.018	-0.89	.376
Creativity	-.688	.008	-87.76	.000	-.688	.008	-87.89	.000	-.688	.008	-87.78	.000
Human Presence	-.557	.013	-42.13	.000	-.556	.013	-42.08	.000	-.557	.013	-42.14	.000
Exposed to Different Ads	.084	.003	30.07	.000	.087	.003	31.10	.000	.084	.003	30.25	.000
Number of Items	2.346	.010	237.40	.000	2.345	.010	237.16	.000	2.346	.010	237.29	.000
Total Spending	.197	.008	24.65	.000	.197	.008	24.64	.000	.197	.008	24.64	.000
Type of Product	.431	.024	17.84	.000	.433	.024	17.94	.000	.431	.024	17.85	.000
Brand Popularity	.110	.006	19.18	.000	.109	.006	19.05	.000	.110	.006	19.18	.000
New Product	1.455	.019	76.64	.000	1.452	.019	76.49	.000	1.455	.019	76.62	.000
Price of Product	-.415	.007	-63.64	.000	-.415	.007	-63.63	.000	-.415	.007	-63.62	.000
Price Cut	.022	.009	2.36	.018	.021	.009	2.26	.024	.022	.009	2.31	.021
Day of Week	.135	.008	16.15	.000	.136	.008	16.27	.000	.135	.008	16.15	.000
Time of Day	-.019	.001	-19.40	.000	-.019	.001	-19.46	.000	-.019	.001	-19.42	.000
Weather	.025	.010	2.35	.019	.024	.010	2.29	.022	.024	.010	2.28	.022
Crowdedness	-.023	.001	-17.90	.000	-.023	.001	-18.23	.000	-.023	.001	-17.87	.000
Type of Appeal	.553	.006	96.50	.000	.552	.006	96.34	.000	.553	.006	96.46	.000
Promotional Signal	.461	.027	16.81	.000	.465	.027	16.94	.000	.462	.027	16.85	.000
Selection Correction	.416	.016	26.72	.000	.416	.016	26.70	.000	.417	.016	26.82	.000
Fixed Effects												
Store	included				included				included			
Month	included				included				included			
Log-likelihood	-1,115,295.10				-1,115,206.40				-1,115,243.30			
N	23,523,924				23,523,924				23,523,924			

Notes: β = unstandardized coefficients, SE = robust standard errors. We do not include a main effect of distance to the screen because we only have this information for exposed shoppers.

Web Appendix N. Effects of Digital Signage on Purchase Quantity

Do exposed shoppers spend more (or less) than shoppers not exposed when they purchase? While the manufacturing brands use digital signage to attract purchases from those that would not purchase otherwise it would nevertheless be interesting to know the effect of digital signage on purchase quantity (Gupta 1988), or in other words spending per shopper on the featured product conditional on purchase. To address this question, we only consider the 311,251 shoppers that purchased focal products to model spending, measured as the total revenue of the exposed product for those that purchased (in Euro). We find no effect of exposure on spending per shopper that purchased (β = .003, *p* = .217), in line with the missing spending effect of digital signage reported by Nanni and Ordanini (2024). This finding is robust when using a truncated regression, and suggests that the positive effects for the brand manufacturers are driven by shoppers buying the focal products that would not buy otherwise, not by shoppers that buy the focal products buying more. In this sense, digital signage seems to work to get trial, i.e. sample the product, and might be used complementary to price discounts that drive purchase quantity.

Table N1: Effects of Digital Signage on Purchase Quantity

	Model 34: Linear Regression				**Model 35: Truncated Regression**			
	β	**SE**	**t**	***p***	**β**	**SE**	**t**	***p***
Digital Signage Effect								
Exposed to Digital Signage	.003	.002	1.23	.217	.003	.002	1.23	.217
Controls								
Wear-out Campaign	.001	.000	13.06	.000	.001	.000	13.16	.000
Learning Effect	.001	.000	108.94	.000	.001	.000	108.95	.000
Temperature	.007	.002	3.18	.001	.007	.002	3.09	.002
Rain	.039	.002	23.26	.000	.039	.002	23.28	.000
Creativity	.252	.007	38.48	.000	.252	.007	38.43	.000
Human Presence	.254	.007	38.74	.000	.255	.007	38.75	.000
Exposed to Different Ads	-.310	.005	-68.36	.000	-.310	.005	-68.26	.000
Number of Items	.097	.005	19.74	.000	.096	.005	19.57	.000
Total Spending	.163	.001	168.92	.000	.163	.001	168.89	.000
Type of Product	-.052	.004	-14.45	.000	-.052	.004	-14.48	.000
Brand Popularity	.017	.003	5.01	.000	.018	.003	5.03	.000
New Product	.003	.000	7.85	.000	.003	.000	7.89	.000
Price of Product	-.024	.004	-5.45	.000	-.024	.004	-5.43	.000
Price Cut	.134	.044	3.05	.002	.137	.044	3.09	.002
Day of Week	2.514	.740	3.40	.001	2.522	.741	3.40	.001
Time of Day	.000	.000	-20.05	.000	.000	.000	-20.11	.000
Weather	.083	.002	51.53	.000	.083	.002	51.63	.000
Crowdedness	.059	.009	6.26	.000	.059	.009	6.28	.000
Type of Appeal	-.041	.002	-24.58	.000	-.041	.002	-24.55	.000
Promotional Signal	-.062	.006	-9.87	.000	-.062	.006	-9.81	.000
Selection Correction	-.245	.007	-33.78	.000	-.247	.007	-33.89	.000
Fixed Effects								
Store	included				included			
Month	included				included			
R-squared / Log-pseudolikelihood	0.339				-282,626.62			
N	311,251				311,251			

Notes: β = unstandardized coefficients, SE = robust standard errors, Spending is log-transformed.

Web Appendix O. Product Switching and Brand Switching

How does exposure influence switching between the featured product and other products of the same brand, and switching between the featured product and competing products from other brands? Previous research decomposed the effect of price promotions for selected products into primary demand effects for the promoted brands, including increased consumption, product switching within the brand, and temporal shifts (which we discuss next), and secondary demand effects for nonpromoted brands (Gupta 1988; Van Heerde, Leeflang, and Wittink 2004).

We relied on the manufacturing brands to obtain global trade item numbers to identify the focal product featured in the ad, other products from the same brand, and competitive products on the sales receipts (i.e., products that directly compete, such as Coke and Pepsi) because the categories provided by the retailer did not allow us such detailed analyses. Unfortunately, most manufacturing brands were only interested in the effect on the focal product. We were able to retrieve data on the effects of digital signage on the focal product, other products from the same brand, and competitive products from 34 campaigns to examine brand switching and product switching, for a total of 9,348,975 shoppers with shopping carts.

Model-free evidence in terms of simple mean comparisons indicates a 77% increase in purchase probability for the focal product and a 16% (24%) increase in purchase probability for other products from the same brand (competitive products). *Prima facie*, this would suggest that the positive effect of digital signage cannot be attributed to product- and brand switching.

Shoppers may purchase the focal product, other products from the same brand, and competitive products at the same time. To formally test product switching and brand switching effects, we use separate logit and probit models for the three outcomes as well as a combined purchase measure. We present the results in Table O1. To ease interpretation, we also discuss the odds ratios.

Being exposed to an ad through digital signage increases the purchase probability of the focal products by 10.1% ($\beta = .124$, $p < .001$) and of other products from the same brand by 8.7% ($\beta = .080$, $p < .001$). It also reduces the purchase probability of competitive products by 12.5% ($\beta = -.134$, $p < .001$). Overall, exposure increases the purchase probability of the category – which includes the focal products, other products from the same brand, and competitive products – by 14.8% ($\beta = .138$, $p < .001$).

These findings suggest three managerial conclusions. First, digital signage at the point of sale creates original demand for the focal products, making it a desirable in-store advertising tool from a product manager's point-of-view. Second, digital signage does not evoke any significant product switching within the same brand but fosters brand switching to the focal brand. Shoppers exposed to an ad for specific products have a higher purchase probability for other products from the same brand and a lower purchase probability for products from competing brands, making digital signage desirable from a brand manager's point-of-view. Third, digital signage for particular products has positive spillover effects on overall category purchase probability. Thus, also from a retailer's point-of-view, the use of digital signage in their stores is desirable.

However, we were not able to consider temporal shifts in shopper behavior in these analyses due to the privacy regulations that prevented us from identifying individual shoppers, which may occur if digital signage would lead to purchase acceleration and stockpiling (Gupta 1988; Van Heerde, Leeflang, and Wittink 2004). We address this question next.

Table O1. Results for Product switching and Brand switching

	Model 36: Focal Product				**Model 37: Other Products**				**Model 38: Competitive Products**				**Model 39: Overall Category**			
	β	**SE**	**z**	**p**	**β**	**SE**	**z**	**p**	**β**	**SE**	**z**	**p**	**β**	**SE**	**z**	**p**
Main Effect																
Exposed to Digital Signage	.124	.006	20.04	.000	.080	.009	8.64	.000	-.134	.008	-16.34	.000	.138	.004	31.35	.000
Controls																
Wear-out Campaign	-.181	.002	-94.04	.000	-.054	.002	-22.75	.000	-.134	.002	-61.08	.000	-.110	.001	-97.96	.000
Temperature	.119	.011	11.29	.000	-.157	.011	-14.08	.000	-.067	.009	-7.29	.000	-.038	.006	-6.31	.000
Rain	.015	.018	0.86	.391	-.122	.025	-4.82	.000	-.072	.026	-2.76	.006	-.023	.013	-1.78	.075
Creativity	-.800	.016	-49.65	.000	-.159	.021	-7.71	.000	.624	.017	36.57	.000	.069	.009	7.89	.000
Human Presence	-1.186	.022	-53.14	.000	4.993	.044	113.87	.000	2.717	.035	78.27	.000	1.657	.015	111.06	.000
Exposed to Different Ads	.205	.004	54.68	.000	-.044	.005	-8.73	.000	-.149	.003	-43.05	.000	.059	.002	27.17	.000
Number of Items	2.368	.012	191.04	.000	1.897	.015	126.96	.000	2.217	.013	170.54	.000	2.170	.008	257.73	.000
Total Spending	.238	.010	23.64	.000	.126	.010	12.90	.000	-.286	.011	-26.79	.000	.070	.007	9.96	.000
Brand Popularity	-.522	.012	-43.95	.000	1.749	.022	79.83	.000	.566	.012	46.13	.000	-.186	.007	-25.78	.000
Price of Product	-.006	.012	-0.51	.609	-1.410	.015	-94.08	.000	-1.671	.013	-131.20	.000	-.223	.006	-34.84	.000
Price Cut	-.133	.010	-13.67	.000	.212	.010	21.43	.000	-.091	.010	-8.70	.000	-.125	.006	-21.06	.000
Day of Week	.116	.008	13.72	.000	-.022	.009	-2.33	.020	-.024	.008	-3.11	.002	.039	.005	7.74	.000
Time of Day	-.004	.001	-3.80	.000	-.001	.001	-0.91	.365	-.014	.001	-14.72	.000	-.008	.001	-12.83	.000
Weather	-.081	.011	-7.47	.000	-.085	.013	-6.55	.000	-.152	.011	-14.03	.000	-.118	.007	-17.27	.000
Crowdedness	-.040	.002	-26.00	.000	.027	.001	19.12	.000	.040	.001	38.23	.000	-.007	.001	-8.84	.000
Type of Appeal	.439	.006	68.97	.000	-1.703	.038	-45.32	.000	-.176	.022	-8.11	.000	-.227	.007	-33.59	.000
Promotional Signal	.243	.019	12.65	.000	-.379	.028	-13.59	.000	-.234	.053	-4.45	.000	.186	.015	12.59	.000
Selection Correction	-.294	.019	-15.17	.000	.065	.024	2.65	.008	.299	.021	14.32	.000	-.311	.012	-25.50	.000
Fixed Effects																
Store	included				included				included				included			
Month	included				included				included				included			
Log-likelihood	-640,828.89				-385,669.26				-531,013.35				-1,341,529.50			
N	9,348,975				9,348,975				9,348,975				9,348,975			

Notes: β = unstandardized coefficients, SE = robust standard errors. We omitted product novelty and the learning effect because of convergence issues and combined June and July due to missing observations.

Web Appendix P. Purchase Acceleration Effects of Digital Signage

Given that we are not able to track shoppers over time, we requested additional data from the specialized company to address the question of whether digital signage leads to purchase acceleration and stockpiling (Gupta 1988; Mela, Jedidi, and Bowman 1998; Van Heerde, Leeflang, and Wittink 2004). Purchase acceleration and stockpiling would happen when the demand from the next period would be realized in the current period, stimulated by digital signage. Thus, the positive effect of digital signage would be offset by a negative effect in the future. We employ a quasi-experimental methodology where we compare the stores from the main analysis with stores without digital signage over a total of 42 weeks to uncover potential purchase acceleration effects evoked by digital signage (Goldfarb, Tucker, and Wang 2022). All these stores are managed by the same retailer, all are relatively similar with respect to their size (around 108,000 square feet) and product assortment, and all are in the same geographical area within Germany. The two ad campaigns investigated ran more than two years after the digital signage systems were installed and during two different times, both used a single ad that was not changed during the campaigns. The campaigns featured two popular stockpiling products with a long stock life that can be stored by consumers: jam and frozen fish. The campaigns were for a novel jam and an existing fish dish, both from large national brands.

Because we were not able to identify shoppers with shopping carts in the control stores due to the lack of RFID readers in these stores, we used the shopping receipts of all 13,625,976 shoppers from all 16 stores during the whole study period. Campaign A (jam) ran for 8 weeks, and a total of 2,770,264 shoppers frequented the stores during this period. Campaign B (frozen fish) ran for 6 weeks, and a total of 2,023,200 shoppers frequented the stores during this period. In order to isolate the purchase acceleration effects of digital signage, we use a difference-in-difference (DiD) regression approach where we specify a pre-treatment period, a treatment period, and a post-treatment period of each 8 weeks (6 weeks) for Campaign A (Campaign B). 2,359,748 (1,881,613) shoppers frequented the stores during the pre-treatment period and 2,685,451 (1,905,700) shoppers frequented the stores during the post-treatment period of Campaign A (Campaign B). The idea is that if purchase acceleration happens, the treatment stores should have a decrease in the post-treatment period because shoppers exposed to digital signage would have purchased the products earlier than they would have normally done.

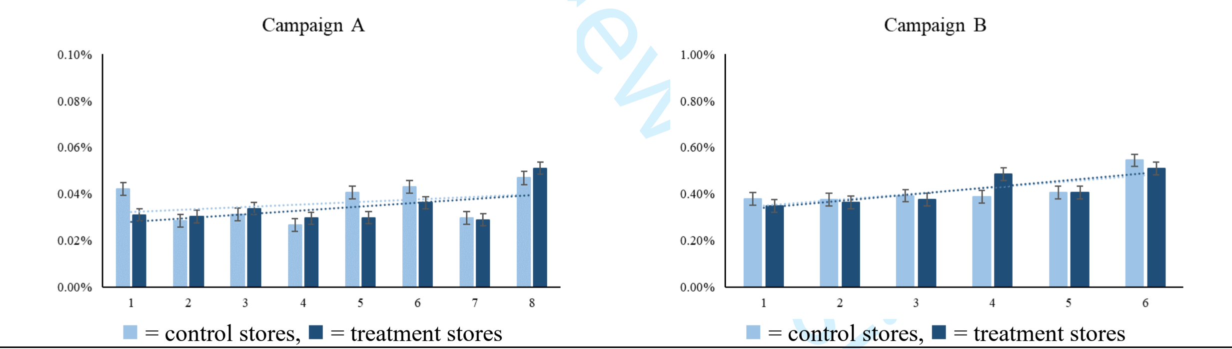
DiD reduces endogeneity concerns because once a digital signage campaign is introduced in the treatment stores, any potential change in the purchase probability should be due to this campaign. That is because additional factors (e.g., the product range in the categories, other advertisements outside the stores, discounts) which could impact purchase probability during the campaign period are either similar in both control and treatment stores or are controlled for. Namely, because we have access to panel data, it is possible to observe shoppers in the same stores, both before and after the treatment and to add fixed effects to control for all store-level, time-invariant heterogeneity such as their specific layout (none of the stores were altered during the study periods). Furthermore, because the data includes several time periods, we add time-specific fixed effects to control for all time-period-specific heterogeneity across all stores such as advertisements outside the stores or the weather. We further add a dummy indicating the presence of price discounts, similar to the main study. Formally, we specify the following DID logistic regression model with time-fixed effects (Goldfarb, Tucker, and Wang 2022):

$$\text{(WA2)} \quad logit(PUR_i) = \beta_0 + \beta_1 Store_i \times Treatment_t + \beta_2 Discount_{it} + \mu_i + \tau_t + \varepsilon_{it},$$

where PUR_i is the purchase of the focal products by shopper i (1 = purchased, 0 = not purchased), β_1 captures the crucial interaction term based on the type of store (1 = with digital signage, 0 = without digital signage) and the time of the treatment (1 = during/after the ad campaign, 0 = before the ad campaign), $Discount_{it}$ controls for the presence of a discount, μ_i is the store-level fixed effect and $\tau_t$is the daily fixed effect, and ε_{it} represents the error. The fixed effects mean that the main effects of $Store_i$ and $Treatment_t$ drop out because they are collinear with the fixed effects. We use the pre-treatment and treatment periods to estimate the immediate effects of digital signage and the pre-treatment and post-treatment periods to estimate the purchase acceleration effects of digital signage.

There are three assumptions that the quasi-experimental setting must fulfill, the Common Trend Assumption (CTA), Stable Unit Treatment Value Assumption (SUTVA), and Conditional Independence Assumption (CIA). The CTA requires that the trend before the treatment is similar for the control and treatment group because then it can be assumed that this would also be the case for the period during and after the treatment (if no treatment would have occurred. We find similar trends in the Pre-Treatment Periods for both campaigns, see Figure O1.

Figure P1: Trends in the Pre-Treatment Period



The SUTVA requires non-interference and treatment consistency. Non-interference means that the treatment is limited to the treatment group and does not influence the control group. It is very likely that this assumption is not violated because the exposure only occurs inside the treatment stores. While it is possible that after being exposed to the advertising campaign in a treatment store the shopper visits a control store afterwards such a behavior is unlikely for several reasons. Individual shoppers are likely to stay with one preferred store because (a) all stores are operated by the same retailer and all have a similar store size, meaning the number of products which are sold in the stores are approximately the same, (b) the stores are all centrally managed by one department, which selects and procures all products, and therefore the product range which is offered in the stores is the same, and (c) any potential price discount is present in all stores, hence shoppers have no monetary incentives to switch between the stores due to price promotions. Treatment consistency requires that the treatment (i.e., the advertising campaign) is the same across all stores and constant over time, which is given because the ad stays the same in all treatment stores and across the entire treatment period.

The CIA requires that the assignment to the treatment group needs to be random and not influenced by other factors. This is inherently difficult for company-related quasi-experimental research as firms always take decisions based on certain, not fully observable criteria. However, after a careful evaluation of relevant factors using the information and data available to us, we argue that the treatment group can considered to be random. Both manufacturing brands had no experience with digital signage before, did not select specific stores with digital signage for their campaigns, booked the digital signage campaigns several months in advance, and used only nationwide print, radio, and TV campaigns that influenced both the treatment and control stores.

The results are reported in Table P1. For the immediate effect of digital signage, we find positive and significant effects for both Campaign A (OR = 1.288, p = .005) and Campaign B (OR = 1.071, p = .011), indicating that digital signage increased the purchase probability for all shoppers in the treatment stores compared to the control stores. This finding underscores the effectiveness of digital signage in driving unplanned purchases.

For the potential purchase acceleration effect of digital signage, we find non-significant effects for both Campaign A (OR = 1.028, p = .787) and Campaign B (OR = 1.020, p = .452), indicating that digital signage does not lead to purchase acceleration and stockpiling of shoppers, in contrast to price discounts (e.g., Van Heerde, Leeflang, and Wittink 2004). We speculate that while price discounts have the urge for shoppers to purchase higher quantities, given the limited availability of the discounts, digital signage has no such effects because no discounts are given. This explanation is in line with our findings for purchase quantity discussed in Web Appendix N.

Table P1: Quasi-Experimental Results

Campaign A	**Model 40: Immediate Effect**				**Model 41: Purchase Acceleration Effect**			
	OR	**SE**	**z**	**p**	**OR**	**SE**	**z**	**p**
Treatment	1.288	0.116	2.82	.005	1.028	0.104	0.27	.787
Discount	4.302	1.208	5.20	.000		n.a.		
Fixed Effects								
Store		included				included		
Day		included				included		
Log-likelihood		-17,828.33				-14,329.45		
N		5,130,012				5,045,199		
Campaign B	**Model 42: Immediate Effect**				**Model 43: Purchase Acceleration Effect**			
	OR	**SE**	**z**	**p**	**OR**	**SE**	**z**	**p**
Treatment	1.071	0.029	2.53	.011	1.020	0.027	0.75	.452
Discount	3.891	0.126	42.12	.000		n.a.		
Fixed Effects								
Store		included				included		
Day		included				included		
Log-likelihood		-131,280.42				-138,107.82		
N		3,904,813				3,787,313		

Notes: OR = odds ratios, SE = standard errors. n.a. = not applicable because there was no price discount during the study period.

Web Appendix Q. Calculating the Value of Digital Signage

Given that we need information on the effect of exposure on focal products, other products from the same brand, and the overall category, we use the 34 campaigns from Web Appendix O to calculate the average value of digital signage. We sometimes must use industry averages rather than actual values in the reported calculations given the non-disclosure agreements with the specialized company, the brand manufacturers, and the retailer.

Calculating the value for retailers. For retailers, digital signage is an investment into the digital screens, the RFID readers, the RFID tags in the shopping carts, and the IT infrastructure that equals I_0. This investment needs to pay off through the retailer's additional revenue stream $\sum_{n=1}^{i} REV_n$, where REV_n are additional revenues in week n that consist of the average gross profit margin of around 3% for the additional sales ADD_n that occur due to digital signage and the in-store advertising revenue ISA_n realized from the brand manufacturers (see Figure 2 in the manuscript). Considering the ongoing costs $COST_n$, digital signage breaks even when:

(WA3) $$I_0 = \sum_{n=1}^{i} (ADD_n \times 0.03) + ISA_n - COST_n\,,$$

where ISA_n and $COST_n$ are given by the retailer but confidential, and ADD_n is calculated using Model 39 in Table O1 with the revenue for the overall category as outcome. We calculate the marginal effect for exposure ($E = 1$) compared to no exposure ($E = 0$) as:

(WA4) $$h(z, \theta) = f(z, \theta | E = 1) - f(z, \theta | E = 0),$$

where θ is the vector of parameters in the model, z is the vector of covariate values, and $f(z, \theta)$ is the scalar-valued function returning the value of the predictor of interest, exposure E. Using mean centering of all other covariates and the weekly demand for digital signage observed in our study (i.e., the advertising pressure), we find that the installation of digital signage in our study breaks even after approximately 1-2 years, depending on the percentage of campaigns for their own brand and for manufacturing brands, and provide additional profit afterwards. The additional weekly revenue after break even for week n are given by:

(WA5) $$REV_n = (ADD_n \times 0.03) + ISA_n - COST_n$$

Our data suggest that on average 87.7% of the additional revenue stems from digital signage and only 12.3% from the additional sales, confirming the value of digital signage highlighted in the business press (Boston Consulting Group 2022; McKinsey & Company 2022).

Calculating the value for brand manufacturers. For brand manufacturers, we measure the advertising elasticity of digital signage as the average percentage change in sales that occurs given a 1% change in advertising expenditure (Sethuraman, Tellis, and Briesch 2011):

(WA6) $$\pi_A = \frac{(SALES_1 - SALES_0) \div (SALES_1 + SALES_0)}{(DIGS_1 - DIGS_0) \div (DIGS_1 + DIGS_0)},$$

where π_A represents the advertising elasticity, $SALES_0$ represents the initial sales on focal products and other products from the same brand that exists when spending on digital signage equals $DIGS_0$, and $SALES_1$ represents the new sales that exists when spending changes to $DIGS_1$. We find an elasticity of 0.18 for digital signage, a value of 50% above the empirical generalizations of short-term brand advertising elasticities of 0.12 reported by Hanssens (2015) and Sethuraman, Tellis, and Briesch (2011). We believe that the proximity to the POS and the unique features of digital signage lead to higher elasticities.

Considering the additional sales ADD_n minus the retailer's average markup of 50% and the costs of exposure CEX_n (i.e., how much a brand manufacturer pays for digital signage, which equals the in-store advertising revenue of the retailer ISA_n plus a markup of the specialized company), a brand manufacturer would make an average gross return AGR_n of 21%:

$$AGR_n = (ADD_n \times 0.50) - CEX_n \quad \text{(WA7)}$$

The value of digital signage with optimization. So far, advertising delivery through digital signage has not yet been optimized. The specialized company will leverage our findings for a better targeting of shoppers to optimize the effectiveness of digital signage, thereby increasing the additional sales ADD_n and π_A. This can be done by focusing exposure to weekends or to the afternoon or evening rather than using all days of the week and all hours of the day equally. In this scenario, increasing the effectiveness and elasticity of digital signage would increase the return of brand manufacturers' expenditures into digital signage AGR_n, allow the retailer to charge a higher price for the exposures to digital signage ISA_n, and in turn shorten the time until the investment into digital signage pays off for the retailer. We outline these relationships in Figure 6 in the manuscript, where we relate changes in REV_n to the break-even point of digital signage for retailers and changes in ADD_n to changes in AGR_n, indicating the potential to charge a higher price for exposure.

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