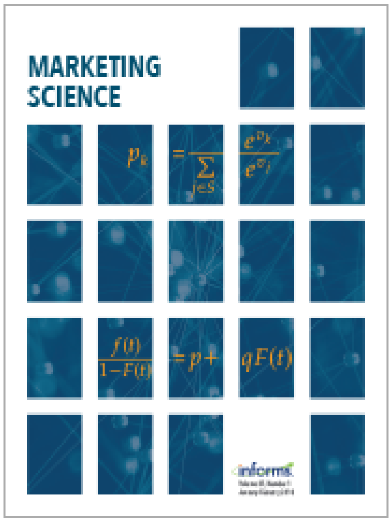

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Effectiveness of Product Recommendations Under Time and Crowd Pressures

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Abstract. Understanding the effects of contextual factors is crucial in designing context-based marketing. This paper focuses on product recommendations and studies how time and crowd pressures—two prominent contextual effects in the consumer behavior literature—can impact the effectiveness of recommendations. Measuring these effects is not straightforward because the joint distribution of consumer choice, time, and crowd pressures is rarely observed outside the laboratory and recommendations are often endogenously determined. We overcome these issues using data from an experiment conducted with vending machines in railway stations across Tokyo. The machines are equipped with a facial recognition system to make recommendations, and recommendations are changed exogenously in the experiment. This setup provides us with well-measured variables of the time and crowd pressures that affect the effectiveness of recommendations. After showing that recommendations increase the sales of both the recommended and nonrecommended products, we show that time pressures moderate the effectiveness of product recommendations for both recommended products directly and nonrecommended products indirectly. Crowd pressures weaken the direct effect on the recommended products, although its impact on the nonrecommended products is small and not robust in some cases. These results indicate that, when marketers make context-based recommendations, they should be mindful of the consumers under time pressure.

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1. Introduction

Marketing communications, such as targeting and search advertisements, have long been based on primarily consumer demographics, product attributes, and past purchase history as used in many online retailers. Recently, however, marketers have paid more attention to context-based marketing because of the increase in the availability of big data and real-time consumer information. A number of firms use context-based advertisements, with which consumers are presented different types of advertisements, depending on their activities at a particular moment and the contextual factors of their environment. For example, the Yelp iOS app displays recommendations based on location, previous check-ins, time of day, and other attributes. Stella Artois uses weather-based, digital, out-of-home billboard advertisements, displaying advertisements only when the temperature at the location is higher than a certain degree.

Because the contexts in public spaces can change frequently, such as in public transportation and at shopping malls, consumer responses to marketing communications can also vary depending on contextual factors. The success of context-based marketing thus depends on how consumers respond to such marketing communications in different contexts. In other words, it is essential to understand how behavioral contextual factors moderate or facilitate the effectiveness of marketing communications. In fact, behavioral marketing studies have shown that contextual factors affect purchasing decisions. For example, consumers might purchase a product that they would not have chosen otherwise when they have only limited time to make purchase decisions (e.g., Nowlis 1995, Dhar and Nowlis 1999) or are under social pressure from the presence of other people in close proximity (e.g., Latane 1981, Argo et al. 2005). However, despite a large number of papers on contextual effects, it is still not well understood whether these contextual effects can affect the effectiveness of marketing communication, especially the effectiveness of product recommendations.

In this paper, we focus on product recommendation as a means of marketing communication and study how contextual factors influence the effectiveness of product recommendations. In particular, we examine the time pressure from having limited time to make purchase decisions and crowd pressure from the presence of other consumers in close proximity. We focus on these two contextual effects because they are prominent examples of contextual factors in the consumer behavior literature, and they exist in many shopping situations in public.

However, we face several challenges in measuring the effectiveness of product recommendations under contextual effects. First, randomization of contextual factors, such as time and crowd pressures, is not easy in the real marketplace. Because an empirical setup from which variables capturing well-defined and well-measured contextual factors are available is very limited, most of the existing studies have used laboratory experiments to examine the effects of time and crowd pressures. We overcome this issue using the setting of beverage purchases from vending machines placed in train stations across the Tokyo metropolitan area, in which the time and crowd pressure variables are well defined and well measured, as we discuss below.

Second, measuring the effects of product recommendations is not straightforward because of endogeneity problems. If a company recommends products based on their (unobserved) popularity, the difference in sales between the recommended and nonrecommended products is confounded by the difference in the baseline popularity of the products. Even within the same product, if a company makes recommendations only at particular times when the company knows that the recommended products sell well, the difference in sales between recommended and nonrecommended times within a product is confounded by the difference in popularity across times. Our study does not suffer from these endogeneity issues because we use data from an experiment in which recommendations are exogenously manipulated and the set of recommended products is exogenously chosen by the researchers.

Our study exploits naturally occurring variations in our context to investigate time and crowd pressures. Because the vending machines used in this study are located on train platforms and in station corridors, consumers tend to feel a high level of time pressure when the next train is approaching, as well as crowd pressure when they purchase in stations with many other people in close proximity. We use the detailed train schedule data to calculate the proxy variables for time pressure and transportation census data to calculate the proxy variables for crowd pressure. Because our proxy variables for time and crowd pressures vary frequently at the minute level and because the unobserved factors affecting sales, such as the demographic composition of passengers, are unlikely to change at the minute level, the variations in our time and crowd pressure variables (after controlling for the time fixed effects) are considered to be exogenous.

Our experimental data come from a company that conducted the experiment in 2013. The company developed new vending machines with product recommendation functionality based on facial recognition and used them in the experiment. In the experiment, we (not the company) randomly selected a set of recommended products and fixed it across the consumers during the period that we study, and then we randomly changed the treatment status at three different times of day (i.e., morning, daytime, and evening). For example, while no recommendations (the control condition) are made on the morning of day 1, an exogenously chosen recommendation (the treatment condition) is made on the morning of day 2. Using this experimental variation in product recommendation, we compare the consumer behaviors with and without recommendations across the different levels of time and crowd pressures.

From the experimental data, we construct two treatment variables to study the effectiveness of recommendations: *product_PR* and *machine_PR*. The first variable indicates whether the product is being recommended or not, whereas the latter indicates whether the vending machine is in a treatment condition.

With these treatment variables, we begin our empirical analysis by examining the impact of product recommendations on the total sales of a vending machine by regressing the machine-level sales on the machine-level treatment variable, i.e., *machine_PR*, to confirm the effectiveness of product recommendations in our setup. After controlling for machine, time-of-day, and day-of-week fixed effects, we find that recommendations increase the total sales of a vending machine by 4.5%, which we call *sales effect*.

We then estimate the product-level models to further investigate the effects of recommendations. In particular, we regress the product-level sales on both *product_PR* and *machine_PR*. Because we include both variables in the model, the coefficient on *machine_PR* captures the indirect effect of making recommendations to nonrecommended products, while the coefficient on *product_PR* captures the direct effect of making a recommendation on the recommended product minus the indirect effect.[1] We call the direct effect on the recommended product *choice effect* and the indirect effect *spillover effect*. Although the spillover effect has not been well studied in the literature, recommendations could attract consumer attention to not only recommended products but also to other products on the menu. Hence, the spillover effect of recommendations could be useful for designing recommendation systems.

We find that both the choice and spillover effects of the recommendations are substantial. The choice effect (the effect of *product_PR*) is 3.8% and the spillover effect (the effect of *machine_PR*) is 3.6%. Hence, the recommendations in our context affect the upper level of the consumer's conversion funnel by drawing more attention to products.

Our main interest is to understand how time and crowd pressures affect the effectiveness of recommendations on machine- and product-level sales. We find that the effectiveness of product recommendations is weakened by 7.5% when the time until the next train decreases by 10% (and hence time pressure increases). Regarding crowd pressure, a 10% increase in the number of passengers around consumers increases the effectiveness of product recommendations only by 0.7%, although this result is not perfectly robust in some specifications as explained below.

To further investigate the channel of the effect, we decompose the machine-level sales effects of recommendations into choice and spillover effects at the product level. We find that the impact is driven not only by the choice effect (direct effect on the recommended products) but also by the spillover effects (on the nonrecommended products). A 10% increase in time pressure weakens the choice effect of recommendations by 0.1% points and weakens the spillover effect by 0.09% points. A 10% increase in crowd pressure weakens the choice effect by 0.15% points. Regarding the spillover effect, this increase in crowd pressure strengthens the spillover effect only by 0.06% points, and this result is not perfectly robust in some specifications. This instability of the spillover effect of crowd pressure explains why its sales effect is not perfectly robust.

We interpret our results regarding time pressure as a natural extension of the findings of Kahneman and Frederick (2002) and Baumeister et al. (1998) that people tend to engage in heuristic decision making under time pressure; that is, under the additional cognitive burden due to recommendations, the simplest heuristic decision is to choose not to make a purchase if such an option is available. Additionally, consumers under time pressure tend to decide what to buy beforehand; hence, they might not want receive recommendations, as suggested by the reactance theory (e.g., Brehm and Brehm 1981). Regarding crowd pressure, our results might indicate that crowd pressure improves the effectiveness of recommendations, consistent with the social impact theory (e.g., Latane 1981, Latane and Wolf 1981), whereas the fact that it is driven by the spillover effect to nonrecommended good indicates that product recommendations might not necessarily have conformity effects, as in the work of Sherif (1935) and Asch (1951).

Our results have three managerial implications. First, we point out the importance of the spillover effects of product recommendations. Recommendations can spill over to the nonrecommended products on the menu, and the spillover effects can vary by the degree of time pressure and crowd pressure. Second, whereas time pressure renders recommendations less effective, crowd pressure enhances the effectiveness. Thus, companies might want to stop using recommendations when consumers are under time pressure, and they might want to increase the intensity of recommendations when consumers are in crowded environments. Third, the choice and spillover effects can have opposite effects with contextual factors. Thus, marketing managers must carefully tailor their recommendations depending on their purposes, such as to increase the sales of a particular product or total sales. In summary, product recommendations can be rendered more effective by considering contextual effects in general. Our results show the importance of contextual effects when designing recommendations.

The remainder of this paper is organized as follows. Section 2 reviews the related literature, and Section 3 discusses time and crowd pressures. Section 4 explains our experimental design and describes summary statistics. Section 5 presents the results. Finally, Section 6 concludes the paper with some discussion of managerial implications.

2. Related Literature

This paper contributes to at least four strands of the literature. First, a large literature investigates empirically the role of recommendations. Ansari et al. (2000) propose a recommendation system based on Bayesian hierarchical models, combining the features of collaborative filtering and content filtering. Ansari and Mela (2003) also consider a model-based collaborative filtering system using Bayesian hierarchical models to tailor customer-level recommendations. As Ansari et al. (2000) state, these systems typically use the past choices of customers, product attributes, expert ratings, and individual characteristics, but not the consumers' contextual environments. Although the recommendation system we use is not as sophisticated as the one used by high-tech online retailers, our simple setup allows us to tease out the effects of contextual factors.

Second, our research adds to the small but growing body of the literature examining the effects of product recommendations on consumer choices. Senecal and Nantel (2004) conduct a series of online choice experiments and find that recommendations significantly affect the likelihood of choosing recommended products (i.e., choice effect in our paper). Bodapati (2008) proposes that recommendation systems should consider sensitivity to a recommendation rather than the baseline probability of purchase because consumers will purchase products that have a higher predicted purchase probability anyway. De et al. (2010) uncover the relationship between consumers' use of recommendation systems and online sales and find that recommendations have positive impacts on sales (i.e., the sales effect in our paper). Our study differs from the above studies in that it exploits the exogenous variation in the set of recommended products and studies how responsive the effectiveness of recommendation is to contextual factors.[2]

Third, because recommendations can be considered a form of advertisement, this study is also related to the literature of context-based advertisement. In the context of mobile advertisements on subway trains, Andrews et al. (2015) show that advertisements on crowded trains increase purchase likelihood. Molitor et al. (2016) show that the distance between consumers and store locations affects the effectiveness of advertisements. Luo et al. (2014) find that the location and time of advertisements affect the purchase decisions of mobile users. We also find that crowdedness reinforces the effectiveness of product recommendations. However, the effectiveness of product recommendations in our setting is found to be much more sensitive to time pressure than crowd pressure.

Fourth, another strand of the related literature considers the effects of time pressure and the presence of other consumers in close proximity. Argo et al. (2005) and Dahl et al. (2001) consider how the presence of other consumers, in terms of both interaction and mere existence, influences consumers based on the theoretical framework of Latane (1981). More recently, Xu et al. (2012) show that consumers choose more distinguished products when they are forced to purchase in a crowded environment. Regarding time pressure, a strand of the literature documents the effects of time pressure on consumer decisions. Dhar and Nowlis (1999) find that time pressure systematically affects consumers' choice deferral. Suri and Monroe (2003) further study how time pressure influences the perception of quality and monetary sacrifices depending on the products' price level. Reutskaja et al. (2011) use an eye-tracker to study the consumers' decision making under time pressure. An exception to the nonlaboratory setup to study the effects of crowd and time pressures is Hui et al. (2009). This study shows that the presence of other consumers attracts consumers to a store zone but reduces overall purchase likelihood. They also find that consumers in a retail setup are more likely to buy if they spend a longer time at the location as consumers feel more time pressure. We also use a nonlaboratory setup, but we study how crowd and time pressures impact the effectiveness of product recommendations in addition to the general effects of the mere existence of other customers.

3. Product Recommendation Under Time and Crowd Pressures

This section introduces some key concepts that we adopt in this paper. We first discuss the general impacts of product recommendations and then examine how time and crowd pressures can influence the effectiveness of recommendations. The discussion helps us to interpret the estimation results later.

3.1. Choice, Spillover, and Sales Effects

The impacts of product recommendations can be, in general, attributed to the product-level direct effect on the recommended product (choice effect) and the indirect spillover effect to nonrecommended product, which comprise the overall sales effect at the store level (or the vending machine level). Whereas the existing papers measure gross effects of making a recommendation on the sales of recommended products, we decompose it into the choice and spillover effect. We explain each effect below.

First, product recommendations can increase the sales of *recommended products* by attracting more consumer attention to these recommended products or by allowing consumers to infer that the products may have high utility. We call this effect on the sales of recommended products the "choice effect."

Second, product recommendations can also affect the purchase probability of other *nonrecommended* products on the same menu (i.e., other products sold in the same vending machine). For instance, product recommendations can cause consumers to examine other available products carefully and generate a spillover of attention to nonrecommended products. We define this spillover effect of recommendations on the consumers' tendency to purchase nonrecommended products on the menu as the "spillover effect." The spillover effect can be explained by using a wide range of economic models such as consumer search models and consideration set models (e.g., Seiler 2013, Zhou 2014, Kawaguchi et al. 2016).

Note that, in this paper, the choice effect is the effect of product recommendation on the sales of the recommended product *on top of* the spillover effect, which comes from the fact that the vending machine recommends some products on each product's sales, whether a product is recommended or not. In the supermarket context, as another example, the spillover effect is the effect that an aisle has in-store displays on each product's sales in the aisle, and the choice effect is the effect of each display's effect on the displayed product's sales, excluding the spillover effect.

Thus, recommendations can cause consumers to examine not only recommended products but also nonrecommended products on the menu. We call the net effect of recommendations at the machine level the "sales effect." The sales effect can increase the total sales of a vending machine to the extent that consumers would purchase a product that they would not have otherwise purchased.

3.2. Time Pressure

The first context effect that we examine is time pressure. Time pressure has been extensively studied in the behavioral literature (e.g., Ben Zur and Breznitz 1981, Dhar and Nowlis 1999) and is known to influence the decision making of consumers in various ways (e.g., Suri and Monroe 2003, Reutskaja et al. 2011). Dhar and Nowlis (1999), for example, find that time pressure leads to choice deferral: When people make choices under time pressure, they are more likely to defer their decisions if such a choice is available. Alternatively, people might want to make fast decisions under time pressure (e.g., Nowlis 1995) to save cognitive resource. The main interest of this study with regard to time pressure is how it influences the effectiveness of product recommendations. Studies by Baumeister et al. (1998) and Kahneman and Frederick (2002) show that people tend to engage in heuristic decision making under time pressure. This tendency may imply that consumers are inclined to follow recommendations to save their limited cognitive resources. However, the implication may differ if the option not to make a choice (not to buy) is available: Consumers may want to avoid making decisions altogether under time pressure because examining recommended products also requires cognitive resources. Time pressure might also decrease the effects of recommendations on the sales of non-recommended products on the menu if consumers feel a pressure to purchase *some* products quickly, but they may also be reluctant to buy recommended products when they have limited time. Another possibility, as reactance theory (e.g., Brehm and Brehm 1981) predicts, is that consumers under time pressure tend to avoid recommended products as they decide before they buy and do not like being told what to buy through recommendations. Thus, how the effectiveness of recommendations is affected by time pressure is an empirical question.

3.3. Crowd Pressure

The second contextual effect that we consider is the influence of the mere presence of other shoppers in close proximity (or around the vending machine, in our case). We call this effect "crowd pressure."[3] In the consumer behavior literature, the theory of social impact (e.g., Latane 1981, Latane and Wolf 1981) and the theory of conformity (Sherif 1935, Asch 1951) suggest that when consumers are surrounded by other consumers, they decide differently and tend to match their behavior to group norms. Hui et al. (2009), for example, find that shoppers in supermarkets tend to visit areas where more shoppers are present because they may infer that there are good products in those areas. Harrell et al. (1980) also find that shoppers tend to follow the traffic pattern of other shoppers. In contrast, social impact can also induce avoidance of shopping because some consumers may hesitate to reveal their purchase in public (e.g., Hui and Bateson 1991). Argo et al. (2005) also find that consumers are less likely to make a purchase if there are too many people around because of a negative feeling.

Regarding the effectiveness of recommendations, the impact of crowd pressure on the choice and spillover effects depends on how consumers feel about following recommendations in the presence of other consumers. On the one hand, when recommendations and choices are visible to other consumers in close proximity, the theory of social impact or conformity may suggest that consumers want to follow product recommendations more as long as the social norm is to follow recommendations. On the other hand, recommendations with the presence of more consumers may be more likely to cause customers to purchase some products, but they may not want to buy the recommended products because these products may not be what they wanted, or they may hesitate to show others that they follow recommendations. It is also possible that attention to recommended products may decrease with the presence of more consumers since a consumer may feel greater pressure from the mere presence of others in very close proximity; hence, he or she might be less able to pay attention to recommendations.

4. Background and Research Design

We first provide background information about our setup and discuss the details of the experimental design, and then we provide summary statistics of the data.

4.1. Background

We study the data of consumers' beverage purchases from vending machines placed at train stations across the Tokyo metropolitan area.[4] The vending machines are owned by a company selling beverages (the company, hereafter); this company is a subsidiary of the largest railroad transportation company in Japan. The railway company operates mainly in the Tokyo metropolitan area and the suburbs of Tokyo. It manages more than 1,700 railway stations, with a daily average of 16 million passengers. The company owns approximately 9,600 vending machines located mostly at railway stations. The annual sales turnover of the company in 2013 was $260 million, with almost the entire sales coming from vending machines. Most of the vending machines of the company sell beverages only, although a small fraction of the vending machines sells snacks and fruit. This study focuses solely on the beverage-selling vending machines.[5]

The vending machines in our study provide a suitable environment for examining the effects of time pressure and crowd pressure. First, the choice situation is simple compared with other setups such as supermarkets, where consumers purchase several products from multiple categories. In our setup, consumers choose a product from a relatively limited choice set. Second, the variables for measuring time and crowd pressures are well defined, with sufficient variation. Although these variables are crucial for studying the contextual effects on recommendations, these variables are usually not available outside laboratories. Third, the vending machines that we use have particular features that are helpful for studying product recommendations, as we explain below.

1. The vending machine has a large digital touch-panel screen in the front, and consumers touch the image of the products that they intend to purchase.

2. The vending machine is equipped with a hidden camera inside the front panel, and the camera captures the consumer characteristics such as age and gender when the consumer stands in front of the vending machine.[6] Then, the vending machine recommends a set of products based on the observed consumer characteristics. Consumers can easily identify the recommended products from the colorful and flashing pop-ups shown for each of the recommended products (see Figures 1 and 2).[7]

The digital display allows the company to change its recommendations more easily than the traditional vending machines or other retail-shopping settings because the company does not have to change the recommendations physically. The set of products recommended to a consumer depends on the consumer's gender and age and can vary by time of day—that is, morning (before 10:00 a.m.), daytime (between 10:00 a.m. and 6:00 p.m.), and nighttime (after 6:00 p.m.). For example, a particular brand of coffee is recommended for male consumers in their forties for the morning. Currently, the set of recommended products for each type of consumers (i.e., gender × age) is the same across all vending machines because the company's system cannot change the set at the individual machine level. Note, however, that the same consumer may face different sets of recommended products when he or she purchases from different vending machines because each machine carries a different set of products.

Figure 1. (Color online) A Vending Machine Used for the Experiment on a Train Platform

Notes. A camera at the top of the machine recognizes the customer's age and gender, and the machine makes recommendations based on the observed consumer characteristics. The image is supplied by the company.

We use *all* of the vending machines with this functionality that the company has installed. Therefore, there is no selection issue in choosing vending machines used for the experiment. There are other types of vending machines, but we do not use them for this study because they do not have recommendation functionality or digital displays.

4.2. Experimental Design

The company ran an experiment, in which it exogenously manipulates the recommendations. In the control condition, no product is recommended, and in the treatment condition, a set of products is recommended. The company executed the treatment and control conditions at three different times of day (i.e., morning, daytime, and nighttime) for weekdays during the week from July 15 to July 26, 2013, as reported in Table 1.

The allocation of the control and treatment conditions across the different times and dates is determined randomly. The allocation is also determined to have sufficient number of treatment timings for each time of the day. In Table 1, the minus sign indicates that the company runs its regular recommendation system, for which the company (not us) chooses products to recommend. The timing of this regular recommendation is also randomized. We do not use these observations because of endogeneity concerns.[8]

The set of recommended products is chosen by us (not by the company) and determined exogenously.[9] It changes across the times of day but remains unchanged across consumers and dates during the observation period so that we can observe the variations within a product. We do so to mitigate the endogeneity concern for measuring the effects of recommendations. If the company recommends products on the basis of the products' (unobserved) popularity, or if it recommends only when the recommended products sell well, then the recommendation effect would be overestimated. In our case, because we can draw a comparison between the sales of a product when it is recommended and when it is not, our estimates are not confounded by the difference in the baseline popularity of the product. Additionally, because the treatment timings are assigned exogenously, our estimates are not confounded by the difference in the popularity of the products across times.

Figure 2. (Color online) An Image of the Touch Panel and Product Recommendations

Notes. The product recommendations are the flashing red bubble signs with the word "Recommended." The image is supplied by the company.

From this experiment, we construct two treatment variables. First, *machine_PR* is a machine-time level indicator variable showing that the machine at the time is under treatment; that is, it shows some recommendations. Second, *product_PR* is a machine-product-time level indicator variable showing that the machine is under treatment at the time *and* the product is recommended. Table 2 provides a breakdown of the number of products recommended by category[10] for the treatment condition.

Now, it is worthwhile to discuss how these variables are related to the choice and spillover effect that we discussed in Section 3. When we analyze product-level sales in Section 5.1 and 5.3, the models include both *machine_PR* and *product_PR*. Hence, when a product is recommended in the treatment, both *machine_PR* and *product_PR* take the value of one, whereas if a product is not recommended but the machine is in the treatment condition, only *machine_PR* takes the value of one. Note that we define the choice effect by the effect captured by *product_PR* and the spillover effect by *machine_PR*. Because we include both variables, *product_PR* captures the pure effect on the recommended product, which does not include the machine-level effect. In other words, *machine_PR* captures only the indirect effect on nonrecommended products (the spillover effect). The previous literature does not consider the direct effect and the indirect effect separately, and it measures the sum of choice effect and spillover effect as the effect of recommendations.

Given this variation, we can estimate the effect of product recommendations by comparing the outcomes of the treatment and control conditions *given* the observable characteristics and machine and/or product fixed effects. The underlying identification assumption for the effectiveness of recommendations is that the treatment status is orthogonal to beverage demand, *conditional on* the time-invariant characteristics of the vending machine (captured by the vending machine and/or product fixed effects) and time-variant observed characteristics, such as temperature and precipitation.

Table 1. Experimental Design

	15	16	17	18	19	22	23	24	25	26
	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
Morning	-	T	-	T	C	C	-	T	C	-
Daytime	T	-	T	C	-	-	T	C	-	T
Nighttime	-	T	C	-	T	T	C	-	T	C

Notes. The number at the top is the day in July 2013, and the second line represents the day of the week. Recommendations for the experiment are executed for treatment T. No product is recommended for control C. In the slot with a bar, the recommendations chosen by the company are implemented, but we do not use the data for these slots in our analysis.

4.3. Variables for Measuring Time and Crowd Pressures

This subsection describes how we construct the proxy variables for time and crowd pressures and the idea

Table 2. Number of Recommended Products in Each Category for the Treatment Condition

	Morning	Daytime	Nighttime
Green tea	1	0	0
Other tea	2	5	2
Soda	2	4	3
Fruit juice	5	2	5
Energy	2	2	2
Coffee	1	2	2
Mineral water	1	0	1
Sports drink	1	0	0
Sweet coffee	0	1	0
Other	0	0	0
Total	15	16	15

underlying them. Observing behavioral outcomes, along with good measurement of time and crowd pressures, is usually not easy outside laboratories. The novelty of our setting is that we can measure the variables for these pressures clearly in real purchase situations, as explained below. The details of the proxy variables' summary statistics are explained in the data section below.

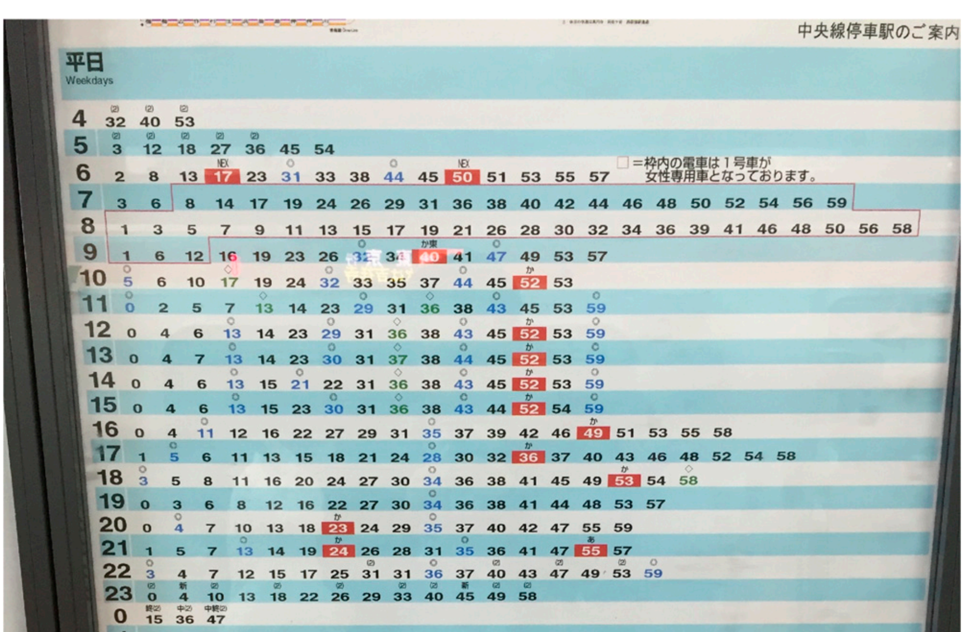
4.3.1. Time Pressure. To measure time pressure, we use a naturally occurring exogenous variation in our setup, *train schedule*. Trains in Tokyo operate punctually, following a rigid time schedule. Figure 3 shows an example of the train schedule of a station. The schedule varies across hours and stations but does not change during weekdays. Most of the passengers are aware of the train schedule because it is displayed at several places in each station. Moreover, electronic bulletin boards at the ticket gate, concourse, and platform of each station display the departure times of the next train and the one thereafter.

To construct proxies for time pressure, we obtain the time schedule of the Japan Railway East on weekdays during the experiment. The data cover all of the trains and stations that the railway company operates. Using the train schedule data, we create an indicator variable, for each minute, that takes the value of one if the time train arrives is within one minute and zero otherwise (*departure*). In addition, we create an indicator variable, for each minute, that takes the value of one if the next train is departing within two minutes but not within one minute and zero otherwise (*departure_next1*). We expect the passengers to experience more time pressure when the train to depart next is approaching now.

Moreover, we take the time until the next train, measured in minutes, as a proxy variable for time pressure (denoted as *time_to_next*). Passengers, however, may not feel much time pressure if the arrival time between the next train and the one that follows is very short (they have no need to wait long in case they miss the next train. Hence, we also consider the arrival time between the next train and the one that follows, denoted as *time_to_after_next*. The variable *time_to_after_next* controls for the commuters' concern about missing the next train. We construct *time_to_next* and *time_to_after_next* by calculating the time by minute until the next train and for the one that follows for each station and for every minute. Thus, these variables for measuring time pressure vary by station and minute.

4.3.2. Crowd Pressure. As discussed in the previous subsection, we consider crowdedness as a measure of crowd pressure. The crowdedness of the purchasing environment in our context is measured by the number of passengers in the station at that time. Figure 4 shows railway platforms when crowded and less crowded. To construct proxies for crowd pressure, we use data from the 2010 *Metropolitan Transportation Census* of the Ministry of Land, Infrastructure, and Tourism (MLIT). MLIT conducts a large-scale survey of passengers every five years for people who use public transportation services to understand the usage and travel patterns of passengers in the Tokyo metropolitan area. The survey asks about the detailed travel paths of

Figure 3. (Color online) A Sample Train Timetable



Notes. Train frequency differs significantly by hour. The figure provides the weekday train timetable of Chuo Line at Mitaka Station.

Figure 4. (Color online) Railway Platforms Where Vending Machines Are Placed

Notes. The figure on the left-hand side corresponds to a less crowded platform in the morning and that on the right-hand side corresponds to a crowded platform in the morning. The figure on the left provided by Hiromi Watanabe and that on the right is from Wikipedia, https://en.wikipedia.org/wiki/Rush-hour.

daily passengers, and we use this information to construct a proxy for how many passengers stay at each station at each moment. More precisely, the survey asks the passengers when they left home, at which station they took a train, when they arrived at the destination, which lines they used, and at which stations they changed trains. The survey covers 1,969 stations and 136 lines in the Tokyo metropolitan area.

We first count the number of passengers departing, changing, or arriving at each station each hour. We call this *crowdedness_hour*. We then use the minute-level variation of the number of passengers departing, changing, or arriving at a station to obtain the minute-level number of passengers at the station. The variable *crowdedness_minute_1* is obtained by counting the number of passengers at each station each minute. Because *crowdedness_minute_1* is calculated from the survey, the number of passengers can be zero for some stations for particular minutes. To interpolate these observations, we estimate a local polynomial regression and predict the number of passengers at each station each minute.[11] We call this variable *crowdedness_minutes_2*.[12]

Given this variation, our empirical strategy to identify the impact of time and crowd pressures on the effectiveness of product recommendations is to compare the treatment effects between the situations with low and high time (crowd) pressures, *conditional on* the observable characteristics, such as temperature and machine, day of week, time of day, and product fixed effects. Hence, the identification assumption for the relationship between time (crowd) pressure and the effectiveness of product recommendations is that time (crowd) pressure is exogenous after controlling for the observable characteristics and various fixed effects.

4.3.3. Validity Checks. We use proxy variables for our analysis as explained above as the time and crowd pressures of the consumers in our data are not directly observable. We think that proxy variables capture the time and crowd pressures in our context reasonably well. Nevertheless, to validate our measures of time and crowd pressures, we conduct two small-scale experiments and use surveys to measure the degree of time and crowd pressures that the subjects experience when purchasing beverages in train stations, in particular the pressures when more people are in proximity and when there is less time until the next train departure.

For our experiments, we recruit undergraduate students from a university in Tokyo and ask them to visit a few stations and purchase beverages from the vending machines in those stations. During their trips, each subject is required to buy beverages and to record the time until the next train and the number of people around the vending machines; these are our measures of time and crowd pressures. The subjects also answer survey questions at the time of their beverage purchases regarding how much time they used and the crowd pressures that they felt. Using the survey responses and measures of time and crowd pressures, we run several linear regression models with individual fixed effects and find that the survey results and our pressure measures are highly correlated, confirming that our proxy measures are valid. The details of the experiment and regression results are reported in the online appendix.

4.4. Limitation of Experimental Design

There are some limitations in the experimental design. Unfortunately, it is not possible for our model to perfectly control for the day-of-week × time-of-day fixed effects, because there are some combinations of day of week and time of day that do not have both treatment and control conditions as Table 1 shows. Hence, there might be some confounds between day of week and time of day, i.e., if there is any event at a certain time of a day of a certain day of a week, such unobserved heterogeneity may not be well controlled. Similarly, it is not possible to control for the date fixed effects because some of the days during the experiment period do not have both a treatment and a control. Hence, if there was any event on a particular date, it is not controlled for in the analysis. However, because the timing of the recommendation is randomly allocated, there should not be any correlation between unobserved heterogeneity and recommendations. Of course, in a finite sample, there still can be an idiosyncratic shock that can confound the effects of recommendations. On the basis of the discussion with the company, we are not aware of any major events that might cause such sizable idiosyncratic shocks, such as train accidents and major delays.

Another limitation of our experimental design is the lack of randomization at the consumer and machine levels, although randomization at these levels can be more informative in estimating the effects of the recommendations. The reason for not taking this path is that the company's current system is not sufficiently flexible to allow for such a design. Although treatment and control conditions are allocated at random, this limitation implies that the result might be sensitive to date-level idiosyncratic shocks, such as a local TV commercial aired when the product recommendations are made. We conduct various robustness checks to ensure that our results are not driven by such unobservable factors. The results of the robustness checks are reported in the online appendix.

Moreover, some confounding factors cannot be ruled out because the variations in time and crowd pressure measures are nonexperimental. In other words, the train schedule and crowdedness may be correlated with the allocation of the treatment condition in the small sample even though allocation was random. We do not think this concern applies because we use the variables that vary with high-frequency to measure the time and crow pressures, while other unobserved factors affecting sales, such as the demographic composition of passengers, are unlikely to change with such high frequency (e.g., the minute level).

In addition, there is a concern for self-selection due to the fact that the randomization is not done at the customer level: Consumers who approach vending machines under high time and crowd pressures may be different from average consumers. For example, consumers who approach the machine under time pressure are different than average because they have already made up their mind what to purchase. To partially address this concern using some observable customer characteristics, we regress sales on the observed characteristics, such as age, gender, and the use of commuter card of the consumers, as well as time and social pressures, for a subset of customers whose characteristics are available. The results show that time and crowd pressures are not correlated with these observed characteristics. Although we cannot rule out the possibility that the pressures are correlated with unobserved consumer characteristics, the results indicate that our pressure measures are not correlated with key observable characteristics.[13] Moreover, we check the robustness of the results by restricting the data into several different subsets of the data. These results can be found in online appendix.

Table 3. Summary Statistics for Stations

	Mean	Std. dev.	Min	Max
No. of machines	2.46	3.03	1	30
Average temperature (Celsius)	25.97	1.56	20	29
Average precipitation (mm)	3.98	2.65	0	12.15

Table 4. Summary Statistics for Vending Machines

	Mean	Std. dev.	Min	Max
Daily no. of sales	179.61	86.00	6	829
Morning	54.88	29.97	1	185
Daytime	73.80	41.41	5	534
Nighttime	51.56	33.19	1	312
No. of available products	30.64	2.58	15	39
No. of recommended products	5.031	1.264	1	10

Lastly, we cannot separately identify the different psychological theories leading to time and crowd pressures,[14] but we can only identify the net effect. Although it is interesting and important to study the impact of each psychological theory separately, our data from the field do not allow for this.

4.5. Data

The data directly come from the company's point-of-sales database for all beverage sales from all vending machines used in the experiment. Table 3 reports the summary statistics of station-level characteristics. We have 187 train stations in our sample and on average 2.5 vending machines per station. The second and third rows report the summary statistics for temperature and precipitation, respectively; we obtained these data from the Japan Meteorological Agency and match them to each station. The average temperature is approximately 26°C, and the average hourly precipitation is approximately 4 mm.

Table 4 reports the summary statistics of characteristics at the vending machine level. The average daily sales figure per machine is approximately 179.6 bottles; this corresponds to a revenue of approximately 20,000 Japanese yen ($200 U.S. dollars).[15] On average, the daytime sales (74 bottles/cans) are greater than the morning and nighttime sales, but this is mainly because the daytime (8 hours) is longer than the morning

(5 hours) and nighttime (6 hours). The average number of available distinct products carried by a machine is approximately 30.6; this is less than the maximum number of slots in a vending machine (36 slots). This is because some products occupy more than one slot per machine. Lastly, on average, five products are recommended in the treatment condition.

Table 5 shows the summary statistics of the proxy variables for time and crowd pressures across stations and minutes for each day. On average, a train departs every 4.2 minutes. Approximately 136 passengers (from the survey samples) pass a station in an hour, and 2 passengers pass a station in a minute.[16] The number of passengers passing a station are larger in the morning and nighttime than in the daytime, whereas the average time to the next train is longest in the morning. However, this is because the morning includes the very early morning hours when the trains do not run frequently.

Lastly, we obtain the consumer demographic information for a subsample of customers. If a customer uses his/her electronic payment card for a purchase instead of cash, the customer's identifier is recorded. In our sample, more than half of the purchases are made using the electronic payment card. A total of 384,762 uniquely identified customers purchased more than 480,000 beverages out of the total sales of 798,300 during the sample period. Of these, 37,144 customers subscribe to the company's reward membership program, and their demographic information such as age and gender is available. We use the customers' demographic information in the robustness check to examine whether customer heterogeneity drives our empirical findings.

4.5.1. Balance Check. Our empirical analysis relies on the assumption that beverage demand is not correlated with the treatment condition conditional on observed characteristics. Although it is not possible to perfectly prove the exogeneity assumption, we can show how observable characteristics vary by the condition.

As Table 6 shows, no systematic difference in observable characteristics exists between the treatment and control conditions.[17]

4.5.2. Graphical Evidence of Average Treatment Effect. Before entering into regression analysis, we provide graphical evidence on the treatment effects. In the left-hand side panel of Figure 5, we show the average machine-level sales per minute for the control (Group 0) and treatment (Group 1) conditions, respectively. The average sales in the treatment condition is greater than that in the control condition by approximately 0.01 units/minute (0.6 units/hour); this difference is statistically significant. In the center panel of Figure 5, we split the sample by the degree of time pressure. More specifically, we split the sample at the median of *time_to_next*; now Group 1 is below the median and Group 2 is above the median. Within each group, Group 0 indicates the control condition and Group 1 indicates the treatment condition. The sales for each time-pressure group is greater for the treatment group than for the control group, and the difference between the treatment and control conditions is greater for Group 2 (less time-pressure group) than for Group 1. Similarly, the right-hand side panel of Figure 5 reports the average sales for the control and treatment conditions by the degree of crowd pressure. We split the sample by *crowdedness_hour* at the median. Again, the sales are greater for the treatment condition in each crowd-pressure subgroup, but the difference of sales between the treatment and control conditions is statistically indistinguishable across the crowd pressure groups. This is because a graphical analysis cannot

Table 5. Summary Statistics for the Number of Passengers and Time to the Next Train

	Variable	Obs.	Mean	Std. dev.	Min	Max
All	*time_to_next*	1,944,970	4.221	6.715	1	90
	crowdedness_hour		135.7	368.4	0	5663
	crowdedness_minute_1		1.674	5.512	0	218
	crowdedness_minute_2		2.006	5.040	0.00127	69.80
Morning	*time_to_next*	586,170	6.590	11.13	1	90
	crowdedness_hour		221.2	549.3	0	5663
	crowdedness_minute_1		2.686	8.023	0	218
	crowdedness_minute_2		2.940	7.027	0.00127	69.80
Daytime	*time_to_next*	782,400	3.282	2.812	1	30
	crowdedness_hour		60.13	152.7	0	2370
	crowdedness_minute_1		0.710	2.203	0	77
	crowdedness_minute_2		1.323	3.109	0.00651	46.50
Nighttime	*time to next*	576,400	3.085	2.669	1	27
	crowdedness_hour		151.3	322.7	0	3754
	crowdedness_minute_1		1.952	5.300	0	183
	crowdedness_minute_2		1.983	4.567	0.00721	42.18

Note. Obs. refers to the number of days × number of machines × minutes at which the proxies are defined.

Table 6. Balance Check

	Control		Treatment	
	Mean	Std. dev.	Mean	Std. dev.
precipitation	3.853	8.91	3.807	9.03
temperature	26.26	1.514	26.168	1.517
crowdedness_hour	337.2	767.4	308.7	703.5
time_to_next	3.436	5.865	3.187	5.163
time_to_after_next	3.481	3.809	3.373	3.73
Female	0.3126	0.4636	0.3227	0.4675
Age 10	0.0148	0.1208	0.0155	0.1235
Age 20	0.1481	0.3552	0.1546	0.3615
Age 30	0.3447	0.4753	0.3469	0.476
Age 40	0.3218	0.4702	0.3191	0.4661
Age 50	0.1623	0.369	0.1639	0.3702

properly control for the observable and unobservable characteristics (through fixed effects). In the next section, we estimate the models that properly take these characteristics into account. Indeed, once other effects are properly controlled, we find that time pressure moderates the recommendation effect of sales.

5. Empirical Analysis

We first study the effect of product recommendation on total sales at the vending machine level (sales effect) and then decompose it into the choice effect and spillover effects in Section 5.1. These analyses show the general effects of product recommendations in our setup. Next, and more importantly, we examine the degree to which time and crowd pressures explain the variations in sales effect (in Section 5.2) and then decompose it into choice and spillover effects (Section 5.3).

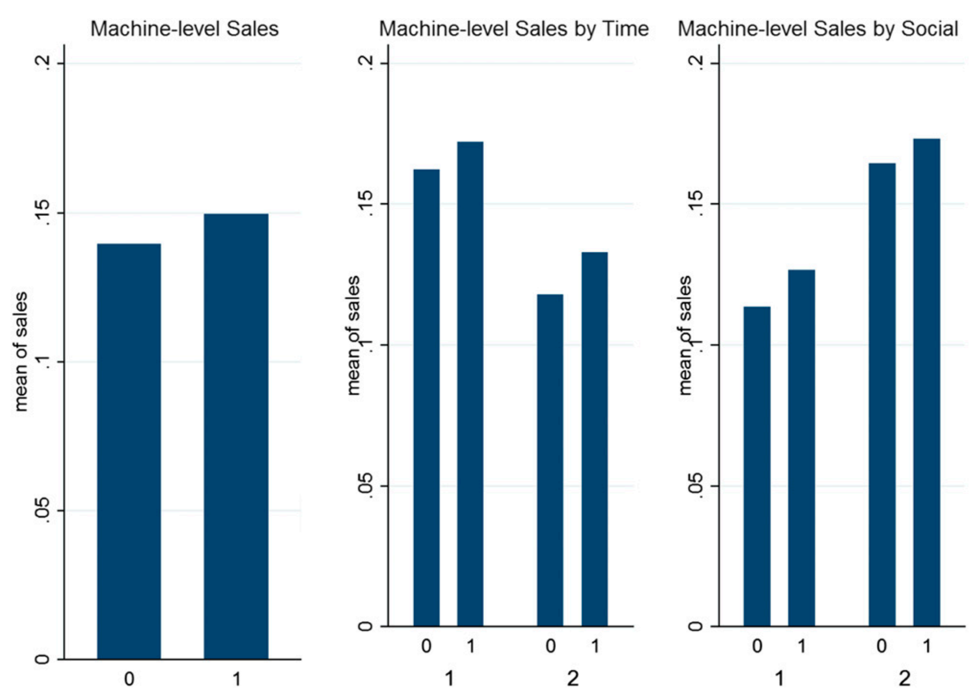
5.1. Baseline Sales, Choice, and Spillover Effects

We first study the sales effect, which is the effect of product recommendations on total sales at the machine level. We run the following Poisson regression:

$$\log E(sales_{kt} \mid machine\_PR_{kt}, x_{kt}, \mu) = \alpha \times machine\_PR_{kt} + x'_{kt}\beta + \mu_t + \mu_k + \mu_d, \qquad (1)$$

where the unit of observation is the vending machine (denoted by the k subscript) in one minute (denoted by the t subscript). The dependent variable $sales_{kt}$ is the total number of beverages sold by vending machine k at minute t. We use Poisson regression because $sales_{kt}$ takes discrete values and can be zero for some vending machines at time t. On the right-hand side, $machine\_PR_{kt}$ is a dummy variable for whether vending machine k is in the treatment condition at time t. The time-varying covariate x_{kt} includes temperature and precipitation. We include them because they may affect beverage demand, particularly when the experiment was conducted, i.e., during the hot and humid summer of 2013. In addition, we include the machine fixed effect μ_k to control for any persistent vending machine and station-level unobserved heterogeneity.

Figure 5. (Color online) Average Effects of Recommendations on Machine-Level Sales



Notes. The left-hand side graph shows the average minute-level sales of vending machines for the control (labeled as 0) and treatment (labeled as 1) conditions. The middle graph splits the control and treatment groups at the median of *time_to_next*, so that Group 1 is less than the median (more time pressure) and Group 2 is greater than the median (less time pressure). The right-hand side graph splits each condition into two groups at the median of *crowdedness_hour* so that Group 1 is less than the median and Group 2 is greater than the median.

We also include the time fixed effect μ_t to control for the time-varying consumer unobserved heterogeneity such as morning commuters or macro-level time shocks.[18] Finally, we include the day-of-week fixed effect μ_d to account for the possibility of consumers' tastes changing over the weekdays. For example, consumers may want to drink more energy drinks on Fridays. We cluster the standard errors at the vending machine level to allow for arbitrary within-machine correlation of the error terms.

Next, we decompose the sales effect of recommendation to the direct effect on the recommended products ("choice effect") and the indirect effect to other products on the menu when the recommendations are made ("spillover effect"). Hence, we use Poisson regression with the following specification:

$$\begin{aligned}\log E(sales_{ikt}|product\_PR_{ikt}, machine\_PR_{kt}, x_{kt}, \mu) \quad (2)\\ = \alpha_1 product\_PR_{ikt} + \alpha_2 machine\_PR_{kt} + x'_{kt}\beta\\ + \mu_i + \mu_k + \mu_t + \mu_d,\end{aligned}$$

where $sales_{ikt}$ is the units of beverage i sold by machine k at time t, and $product\_PR_{ikt}$ is a dummy variable indicating whether beverage i at vending machine k is recommended at time t (i.e., minute). The variable $machine\_PR_{kt}$ is similarly defined as Equation (1), and the time-varying covariate x_{kt} includes temperature and precipitation. Thus, α_1 captures the choice effect, and α_2 captures the spillover effect. The model also controls for the product, machine, time, and day-of-week fixed effects. The product fixed effect absorbs the time-invariant product-level unobserved heterogeneity, such as the popularity of each brand. Finally, we cluster the standard errors at the machine level to account for arbitrary within-machine correlation of the error terms.

Several comments are in order. First, the models do not include price because there is no within-product price variation across times and locations, and product dummies absorb all of the product-specific price effects in the estimation. Second, the machine, product, time, and day-of-week fixed effects capture much of the unobserved consumer heterogeneity, such as the popularity of some locations or products and the composition of consumer types (i.e., commuters), which may vary across times and locations. Third, we choose not to estimate a consumer-level discrete choice model because it is computationally infeasible to estimate at the minute level with all of the fixed effect parameters. Fourth, we do not adopt a matching estimator. Matching estimators are useful to control for selection biases in the treatment condition based on observable characteristics if one can credibly find almost identical clones. In our setting, the observable characteristics that can be used to match the machines are temperature and precipitation, which vary by time and machine, but unfortunately these variables are not sufficient to credibly match the machines or consumers.[19]

Table 7 presents the estimation results for Equation (1). Model 1 includes the time fixed effect (i.e., morning, daytime, and nighttime) in addition to the machine and day-of-week fixed effects, whereas Model 2 has the hour fixed effects to further control for consumer unobserved heterogeneity, but the results are both quantitatively and qualitatively very similar to each other. Both models find that recommendations increase the total sales of a machine by 4.5%. In addition, we find that weather conditions affect beverage sales significantly.

Next, Table 8 reports the results of Equation (2). Again, regarding μ_t, Model 1 controls for the time-of-day fixed effect, and Model 2 controls for the hour fixed effect.[20] We find that product recommendations have a positive choice effect on sales of the recommended products. Moreover, product recommendations have a very strong positive impact on sales of nonrecommended products; the spillover effect is positive. Recommendations increase the sales of the recommended products by 3.84% through the choice effect, which does not account for the spillover effect, and the sales of the nonrecommended products by 3.64% (spillover effect).[21] This spillover effect explains the large increase in machine-level sales with recommendations, as shown in Table 7.

5.2. Time and Crowd Pressures on Machine-Level Sales

We now extend the baseline model in the previous subsection to examine the effects of the time and crowd pressures on machine-level sales. The estimation equation is as follows:

$$\begin{aligned}&\log E(sales_{kt}|D_{kt}, time_{kt}, crowd_{kt}, x_{kt}, \mu) \quad (3)\\ =\ &\alpha_1 \times machine\_PR_{kt} + \alpha_2 \times (machine\_PR_{kt} \times time_{kt})\\ &+ \alpha_3 \times (machine\_PR_{kt} \times crowd_{kt}) + \alpha_4 \times time_{kt}\\ &+ \alpha_5 \times crowd_{kt} + x'_{kt}\beta + \mu_k + \mu_d + \mu_t.\end{aligned}$$

Table 7. Machine-Level Poisson Regression Results

	Model 1 Poisson	Model 2 Poisson
temperature	0.0794***	0.0794***
	(0.00316)	(0.00316)
precipitation	-0.00219***	-0.00219***
	(0.000372)	(0.000372)
machine_PR	0.0441***	0.0441***
	(0.00367)	(0.00367)
Constant	-3.715***	-5.817***
	(0.0855)	(0.103)
Observations	3,399,480	3,399,480

Notes. Standard errors are in parentheses and are clustered at the machine level. Both models contain machine and day-of-week fixed effects. Model 1 includes time (morning, daytime, nighttime) fixed effect in addition, and Model 2 includes hour fixed effect.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 8. Product-Level Poisson Regression Results

	Model 1 Poisson	Model 2 Poisson
temperature	0.0798***	0.0801***
	(0.00305)	(0.00306)
precipitation	-0.00189***	-0.00186***
	(0.000353)	(0.000356)
machine_PR	0.0377***	0.0377***
	(0.00377)	(0.00377)
product_PR	0.0358***	0.0366***
	(0.00903)	(0.00899)
Constant	-7.330***	-8.339***
	(0.104)	(0.114)
Observations	108,188,100	108,188,100

Notes. Standard errors are in parentheses and are clustered at the machine level. Both models contain machine and day-of-week fixed effects. Model 1 includes the time (morning, daytime, nighttime) fixed effect in addition, and Model 2 include the hour fixed effect.
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

The outcome variable is the total sales of vending machine k at minute t. The extended model includes the newly created variables for time and crowd pressures (i.e., *time* and *crowd*, respectively), as well as the interaction terms between these variables and treatment dummy, $machine\_PR_{kt}$. Because we have three different variables to measure time and crowd pressures, respectively, we try all combinations of these: *time* ∈ {*departure*, *departure_next1*, {*time_to_next*, *time_after_next*}} and *crowd* ∈ {*crowdedness_hour*, *crowdedness_minute_1*, *crowdedness_minute_2*}. In addition, the model controls for temperature and precipitation, as well as the vending machine, day-of-week, and time-of-day fixed effects (i.e., morning, daytime, and nighttime). Finally, as in the previous section, we cluster the standard errors at the vending machine level.

Table 9 reports the estimation results for Equation (3) with *crowdedness_hour*. To save space, we report the results with *crowdedness_minute_1* and *crowdedness_minute_2* in Tables A.3 and A.4, respectively, in the online appendix. The results are qualitatively unchanged by the choice of *crowd* variable. In Table 9, the model in the first column considers *departure* as the proxy for time pressure, and the models in the second and third columns use *departure_next1* and *time to next*/*time to after next*, respectively.

We start our discussion from the interaction between product recommendation and time pressure. The effects of time pressure on the effectiveness of recommendations are estimated consistently across all of the specifications. The coefficients for the interaction term between *machine_PR* and each of the variables for time pressure (*departure*, *departure_next1*, and *time to next*, and *time_to_after_next*) show that the effectiveness of recommendation on the recommended product is weaker when consumers are under time pressure: The coefficients on *machine_PR* × *departure* and *machine_PR* × *departure_next1* are both negative and statistically significant. The coefficient on *machine_PR* × *time to next* is estimated to be positive and statistically significant, indicating that the sooner that the next train leaves, the smaller that the effectiveness is of recommendations. We also find that *machine_PR* × *time after next* is not statistically significant. Hence, the time until the train after the next one does not change the effectiveness of product recommendations. Overall, recommendations are more effective in increasing overall sales when the time pressure is low.

We then discuss the interaction between product recommendations and crowd pressure. The coefficients on the interaction term between *machine_PR* and *crowdedness_hour* in the sixth row of Table 9 are positive and statistically significant, although the coefficients are very small. As reported in Tables A3 and A4 in the online appendix, we find similar results for the interaction between *machine_PR* and *crowd* when we use *crowdedness_minute_1* and *crowdedness_minute_2* in place of *crowdedness_hour*. The estimated coefficients indicate that product recommendations increase the total sales of vending machines when consumers experience more crowd pressure.

The average marginal effect of *machine_PR* is calculated as 4.5%, according to the specification with *crowdedness_hour* for crowdedness pressure and time until the next train for time pressure. The effectiveness of product recommendations is reinforced by 0.03% points if the number of passengers around a consumer increased by 10% from the mean and is reinforced by 0.43% points if the time until the next train increases by 10%. In conclusion, crowd pressure reinforces the effectiveness of product recommendation, whereas time pressure weakens it. Moreover, the effectiveness of product recommendation is more elastic to a change in time pressure than crowd pressure.

Finally, one might wonder whether crowd pressure and sales might have different patterns in a day across vending machines and the residuals after controlling for machine and time fixed effects might be still correlated. To see whether this concern changes our results, we further add machine-timing fixed effects.[22] The results are reported in Table 10 for *crowdedness_hour*. The results for *crowdedness_minute_1* and *crowdedness_minute_2* are reported in Tables A5 and A6, respectively in the Online Appendix. We find that all of the results in Table 9 remain robust except for the effects of crowd pressure on the effectiveness of product recommendations. The coefficients on *machine_PR* and *crowdedness_hour* are very small and statistically insignificant. To further investigate why such a pattern emerges, we consider these effects by decomposing it into choice and spillover effects at the product level in the next subsection.

Table 9. Machine-Level Poisson Regression Results with Hour Crowdedness

	Model 1	Model 2	Model 3
temperature	0.0792***	0.0792***	0.0785***
	(0.00315)	(0.00315)	(0.00318)
precipitation	-0.00186***	-0.00189***	-0.00203***
	(0.000371)	(0.000372)	(0.000376)
machine_PR	0.0668***	0.0660***	0.00345
	(0.00504)	(0.00519)	(0.00682)
crowdedness_hour	0.000159***	0.000154***	0.0000873***
	(0.0000117)	(0.0000117)	(0.0000110)
departure	0.204***		
	(0.0101)		
machine_PR × *crowdedness_hour*	0.0000158***	0.0000146***	0.00000976**
	(0.00000307)	(0.00000318)	(0.00000345)
machine_PR × *departure*	-0.0644***		
	(0.00677)		
departure_next1		0.269***	
		(0.00947)	
machine_PR × *departure_next1*		-0.0599***	
		(0.00756)	
time_to_next			-0.0822***
			(0.00248)
time_to_after_next			-0.0588***
			(0.00281)
machine_PR × *time_to_next*			0.0126***
			(0.00142)
machine_PR × *time_to_after_next*			0.00254
			(0.00139)
Constant	-3.820***	-3.829***	-2.942***
	(0.0864)	(0.0862)	(0.0879)
Observations	3,399,480	3,399,480	3,146,045

Notes. Standard errors are reported in parentheses and clustered at the machine level. Machine, day-of-week, and time (morning, daytime, nighttime) fixed effects are controlled for.

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$.

5.3. Context Effects on Product-Level Choice and Spillover Effects

Finally, we decompose the sales effects of crowd and time pressures into the direct choice effect and the indirect spillover effect. By extending the model in Equation (2), we run the following Poisson model:

$$\log E(sales_{ikt}|product_{ikt}, machine\_PR_{kt}, time_{kt}, crowd_{kt}, x_{kt}, \mu) \tag{4}$$

$$\begin{aligned} &= \alpha_1 product\_PR_{ikt} + \alpha_2 machine\_PR_{kt} \\ &\quad + \alpha_3(product\_PR_{ikt} \times time_{kt}) \\ &\quad + \alpha_4(product\_PR_{ikt} \times crowd_{kt}) \\ &\quad + \alpha_5(machine\_PR_{kt} \times time_{kt}) \\ &\quad + \alpha_6(machine\_PR_{kt} \times crowd_{kt}) + \alpha_7 \times time_{kt} + \alpha_8 \\ &\quad \times crowd_{kt} + x'_{kt}\beta + \mu_i + \mu_k + \mu_d + \mu_t, \end{aligned}$$

where all of the terms are defined in the same way as above and the standard errors are clustered at the machine level. Regarding time pressure, α_3 captures the choice effect and α_5 captures the spillover effect. Similarly, α_4 corresponds to the choice effect of crowd pressure and α_6 corresponds to the spillover effect. The product, machine, day, and time fixed effects are included as well. Note that *product_PR* captures the direct effect of the product recommendation on the recommended products (excluding the spillover effect) and *machine_PR* captures the indirect effects of product recommendations on all of the products in the vending machine including nonrecommended products.

Table 11 presents the estimation results of Equation (4) for *crowdedness_hour*, and Tables A.7 and A.8 in the online appendix, respectively, present the results for *crowdedness_minute_1* and *crowdedness_minute_2*. As in the previous section, each column in these three tables uses a different combination of proxy variables for time and crowd pressures.

We start with the discussion of the effect of time pressure. We find the same pattern as with the effect on sales; The choice effect of time pressure and the spillover effect are both negative and statistically significant. Hence, time pressure moderates both the choice and spillover effects, resulting in recommendations reducing the total sales as time pressure increases.

Table 10. Poisson Regression Results: Machine-Level, Hour Crowdedness, Machine × Time (Morning, Daytime, Nighttime) Fixed Effects

	Model 1	Model 2	Model 3
temperature	0.0784***	0.0784***	0.0771***
	(0.00298)	(0.00298)	(0.00304)
precipitation	-0.00276***	-0.00276***	-0.00284***
	(0.000363)	(0.000364)	(0.000372)
machine_PR	0.0734***	0.0724***	0.00807
	(0.00499)	(0.00508)	(0.00626)
crowdedness_hour	0.000259***	0.000250***	0.000156***
	(0.0000169)	(0.0000166)	(0.0000134)
departure	0.179***		
	(0.00951)		
machine_PR × *crowdedness_hour*	-0.00000237	-0.00000329	-0.00000656
	(0.00000320)	(0.00000337)	(0.00000357)
machine_PR × *departure*	-0.0652***		
	(0.00627)		
departure_next1		0.245***	
		(0.00905)	
machine_PR × *departure_next1*		-0.0605***	
		(0.00701)	
time_to_next			-0.0802***
			(0.00238)
time_to_after_next			-0.0581***
			(0.00257)
machine_PR × *time_to_next*			0.0123***
			(0.00134)
machine_PR × *time_to_after_next*			0.00312*
			(0.00130)
Constant	-3.873***	-3.886***	-3.010***
	(0.0764)	(0.0762)	(0.0794)
Observations	3,399,480	3,399,480	3,146,045

Notes. Standard errors are clustered at the machine level and reported in parentheses. Day-of-week fixed effects and machine × time (morning, daytime, nighttime) fixed effects are controlled.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Regarding the effect of crowdedness, we show in Table 9 that the effect of recommendation on total machine-level sales tends to be stronger when the sales area is more crowded. By decomposing the effects of recommendations into the choice and spillover effects, we find that the choice effect attenuates the effectiveness, whereas the spillover effect enhances it. Hence, consumers under crowd pressure are more likely to buy *some* products from the vending machine, but the pressure attenuates the effectiveness of recommendations for the recommended products. The differential choice and spillover effect effects (and sales effect) may have large implications when firms decide which products to recommend.

We calculate the marginal effects. A 10% increase in time pressure weakens the choice effect of recommendation by 0.1% points and weakens the spillover effect by 0.09% points. A 10% increase in crowd pressure weakens the choice effect by 0.15% points while strengthening the spillover effect by 0.06% points.

Finally, we control for product- and machine-timing fixed effects.[23] In Section 5.2, we find that the coefficients of the machine-level regression are robust to adding machine-timing fixed effects except for the coefficient on *machine_PR* × *crowdedness_hour*. Here, we examine whether there is a similar pattern in the product-level regression.

Table 12 reports the results when machine-timing fixed effects are added. We also estimate the same specification with *crowdedness_minute_1* and *crowdedness_minute_2*, respectively, and report the results in Table A9 and A10 in the online appendix. We find that the results on time pressures remain unchanged to the introduction of machine-timing fixed effects. Moreover, the effect of crowd pressure on the *choice effect* is robust to adding machine-timing fixed effects. The effect of crowd pressure on the spillover effect of recommendation is, however, not robust, partly because the magnitude of the effect is very small, and one requires a much larger-scale experiment for identifying

Table 11. Product-Level Poisson Regression with Hour Crowdedness

	Model 1	Model 2	Model 3
temperature	0.0797***	0.0797***	0.0797***
	(0.00306)	(0.00306)	(0.00334)
precipitation	-0.00156***	-0.00156***	-0.00208***
	(0.000351)	(0.000351)	(0.000415)
crowdedness_hour	0.000156***	0.000156***	0.0000875***
	(0.0000123)	(0.0000123)	(0.0000116)
machine_PR	0.0494***	0.0482***	0.0224***
	(0.00494)	(0.00499)	(0.00559)
product_PR	0.0801***	0.0793***	0.0546***
	(0.0113)	(0.0112)	(0.0129)
departure	0.196***		
	(0.0120)		
machine_PR × *crowdedness_hour*	0.0000270***	0.0000264***	0.0000179***
	(0.00000309)	(0.00000307)	(0.00000337)
product_PR × *crowdedness_hour*	-0.0000684***	-0.0000687***	-0.0000647***
	(0.00000871)	(0.00000871)	(0.00000946)
machine_PR × *departure*	-0.0499***		
	(0.00662)		
product_PR × *departure*	-0.0351**		
	(0.0133)		
departure_next1		0.195***	
		(0.0120)	
machine_PR × *departure_next1*		-0.0466***	
		(0.00677)	
product_PR × *departure_next1*		-0.0330*	
		(0.0132)	
time_to_next			-0.000708***
			(0.000197)
time_to_after_next			-0.00116
			(0.000675)
machine_PR × *time_to_next*			0.000346*
			(0.000162)
machine_PR × *time_to_after_next*			0.000890
			(0.000801)
product_PR × *time_to_next*			0.000656**
			(0.000292)
product_PR × *time_to_after_next*			-0.00170
			(0.00155)
Constant	-7.442***	-7.441***	-7.176***
	(0.105)	(0.105)	(0.115)
Observations	108,188,100	108,188,100	81,508,362

Notes. Standard errors are reported in parentheses and are clustered at the machine level. Day-of-week, time (morning, daytime, nighttime), machine, and product fixed effects are controlled.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

such a small effect. Thus, the unstable result of the effect of crowd pressure in the machine-level regression in Section 5.2 results from the unstable estimate on the spillover effect of crowd pressure.

Table 13 reports the results when product-timing fixed effects are added. Similar to the above, we also estimate the same specification with *crowdedness_minute_1* and *crowdedness_minute_2* and report the results in Table A11 and A12 in the online appendix. The table shows that the results are quite similar to those in Table 11. Hence, our results are robust to adding product-timing fixed effects.

In addition to the analysis above, we also check the robustness of our main results in various ways. The details of the robustness checks can be found in the online appendix, and our further analysis confirms that our results are qualitatively robust in terms of (i) functional form assumptions and (ii) unobserved customer heterogeneity. Regarding the unobserved customer heterogeneity, we take advantage of the

Table 12. Product-Level Poisson Regression Results with Hour Crowdedness and Machine × Time (Morning, Daytime, Nighttime) Fixed Effects

	Model 1	Model 2	Model 3
temperature	0.0791***	0.0791***	0.0795***
	(0.00289)	(0.00289)	(0.00315)
precipitation	-0.00245***	-0.00245***	-0.00316***
	(0.000344)	(0.000344)	(0.000409)
crowdedness_hour	0.000261***	0.000261***	0.000179***
	(0.0000172)	(0.0000172)	(0.0000145)
machine_PR	0.0574***	0.0577***	0.0287***
	(0.00498)	(0.00499)	(0.00547)
product_PR	0.0651***	0.0645***	0.0484***
	(0.0109)	(0.0109)	(0.0126)
departure	0.169***		
	(0.0114)		
machine_PR × crowdedness_hour	0.00000431	0.00000446	-0.00000515
	(0.00000342)	(0.00000343)	(0.00000365)
product_PR × crowdedness_hour	-0.0000306**	-0.0000308**	-0.0000236*
	(0.00000963)	(0.00000962)	(0.0000101)
machine_PR × departure	-0.0530***		
	(0.00642)		
product_PR × departure	-0.0166		
	(0.0135)		
departure_within1		0.171***	
		(0.0114)	
machine_PR × departure_next1		-0.0539***	
		(0.00640)	
product_PR × departure_next1		-0.0150	
		(0.0136)	
time_ to_next			-0.000264
			(0.000180)
time_to_after_next			0.000225
			(0.000624)
machine_PR × time_to_next			0.000515***
			(0.000151)
machine_PR × time_to_after_next			-0.000336
			(0.000905)
product_PR × time_to_next			0.000337
			(0.000284)
product_PR × time_to_after_next			-0.0000506
			(0.00172)
Constant	-7.515***	-7.516***	-7.181***
	(0.0970)	(0.0970)	(0.107)
Observations	108,188,100	108,188,100	81,508,353

Note. Standard errors are reported in parentheses and are clustered at the machine level. Day-of-week, machine × time (morning, daytime, nighttime), and product fixed effects are controlled.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

information about customer demographics, use of debit cards for purchase, and location of vending machines. These robustness checks confirm that our main results are not driven by potential selection issues due to unobserved consumer heterogeneity.[24]

6. Managerial Implications and Conclusion

This paper studies the effectiveness of product recommendations and its sensitivity to time and crowd pressures. To overcome the challenges in measuring the impacts of time and crowd pressures on the effectiveness of product recommendations, we conduct field experiment in which recommendations are made exogenously. The setup of beverage purchases from vending machines placed in train stations provides us with well-measured proxies for time and crowd pressures.

We find that product recommendations increase sales of not only the recommended products, as the previous literature has shown but also of nonrecommended

Table 13. Produce-Level Poisson Regression with Hour Crowdedness and Product × Time (Morning, Daytime, Nighttime) Fixed Effects

	Model 1	Model 2	Model 3
temperature	0.0794***	0.0794***	0.0795***
	(0.00304)	(0.00304)	(0.00327)
precipitation	-0.00157***	-0.00157***	-0.00209***
	(0.000346)	(0.000346)	(0.000404)
crowdedness_hour	0.000157***	0.000157***	0.0000892***
	(0.0000122)	(0.0000123)	(0.0000116)
machine_PR	0.0437***	0.0440***	0.0191***
	(0.00495)	(0.00495)	(0.00561)
product_PR	0.139***	0.139***	0.0957***
	(0.0117)	(0.0117)	(0.0132)
departure	0.195***		
	(0.0120)		
machine_PR × *crowdedness_hour*	0.0000202***	0.0000204***	0.0000114***
	(0.00000315)	(0.00000317)	(0.00000345)
product_PR × *crowdedness_hour*	-0.0000251**	-0.0000254**	-0.0000209*
	(0.00000893)	(0.00000894)	(0.00000981)
machine_PR × *departure*	-0.0480***		
	(0.00662)		
product_PR × *departure*	-0.0534***		
	(0.0136)		
departure_within1		0.198***	
		(0.0120)	
machine_PR × *departure_next1*		-0.0489***	
		(0.00662)	
product_PR × *departure_next1*		-0.0519***	
		(0.0138)	
time_to_next			-0.000695***
			(0.000195)
time_to_after_next			0.000100
			(0.000629)
machine_PR × *time_to_next*			0.000356*
			(0.000157)
machine_PR × *time_to_after_next*			-0.000301
			(0.000904)
product_PR × *time_to_next*			0.000982***
			(0.000280)
product_PR × *time_to_after_next*			0.000128
			(0.00170)
Constant	-7.941***	-7.941***	-7.744***
	(0.171)	(0.171)	(0.166)
Observations	108,188,100	108,188,100	81,508,353

Notes. Standard errors are reported in parentheses and are clustered at the machine level. Day, machine, and product × time fixed effects are controlled.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

products. The recommendations can spill over to other products in the same menu. This result implies that marketing managers should take not only the choice effect of recommendation but also the spillover effect of recommendations into account in designing product recommendation.

More importantly, we find that time and crowd pressures impact the effectiveness of recommendations. Our results show that time pressure attenuates both the choice and spillover effects. That is, consumers under time pressure are less likely to buy both recommended and nonrecommended products. In terms of financial implications, the estimates imply that the profits can increase by 500,000 JPY per day if the company stops any recommendation when there is more time pressure.[25] These findings can be considered a natural extension of the Dhar and Nowlis (1999) finding in the sense that providing additional information through product recommendation does not render decision making under time pressure easier. Our findings may also be consistent with the Kahneman and Frederick (2002) findings that people tend to engage in heuristic decision making under time pressure, in that the simplest heuristic decision, especially under the additional cognitive burden due to recommendation, is not to make a choice if such an option is available. Managers can avoid using recommendations on time-limited purchase occasions. Conversely, companies can benefit from increasing the intensity of recommendations for consumers in a crowded environment.

Crowd pressure has a differential impact on choice and spillover effects. We find that crowd pressure weakens the choice effect of recommendation. In contrast to the choice effect, the spillover effect strengthens the effects on nonrecommended products, although the result may not necessarily be robust in some cases. One way to interpret this outcome is that engaged customers are more likely to make a purchase under crowd pressure, but the recommended product may not necessarily be what they want; hence, the spillover effect arises to the nonrecommended products. Thus, managers should carefully tailor the recommendations when purchasing occasion is such that presence of other customer affects consumer's decision.

Finally, there are some limitations in this study. First, this study does not allow us to distinguish the different psychological theories underlying time and crowd pressures. Identifying the exact psychological mechanisms underlying the results would provide useful suggestions for the design of product recommendations, but this is beyond the scope of this study. Second, our findings do not necessarily imply that time and crowd pressure effects exist in other situations. Investigating the boundary conditions under which these contextual factors play roles could be an interesting and important research question, given the rapid increase in context-based marketing.

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Endnotes

[1] Hence, if a product is recommended, both *product_PR* and *product_PR* are one, whereas if a product is not recommended but the machine is in the treatment, only *machine_PR* is one.

[2] Kawaguchi et al. (2016) is a companion paper, in which we separately attribute the effects of recommendations on preference and consumer attention by structurally estimating a consideration set model and proposing a new identification source for consideration set models.

[3] Note that this phenomenon is different from social interaction (e.g., Manski 1993, Bollinger and Gillingham 2012), in which people are affected by the behavior of other people.

[4] The vending machine is one of the main beverage sales channels in Japan. Approximately 35% of the total beverages sales occur through vending machines. There were approximately 2.6 million vending machines in 2013 (i.e., one vending machine for every 50 people).

[5] The vending machines sold only cold beverages during the observation period (i.e., the summer of 2013).

[6] Cameras are used only to identify the consumer characteristics for making product recommendations. Because of privacy concerns, the company does not record the information collected by the camera, including the consumer characteristics.

[7] Note that consumers can see all of the available products on the display regardless of whether they are recommended or not.

[8] Note that we have a relatively small number of control groups compared with treatment groups, but it does not bias our estimates because the treatment groups are allocated exogenously. However, it might affect the accuracy (standard errors) of estimates.

[9] The set of recommended products are randomly selected by the authors from the set of products excluding products with very low sales given that the system allows only limited number of products to be recommended. The average sales of recommended products in the pre-experiment period are not statistically different from those of nonrecommended products.

[10] The definition of categories is determined by the company. The category-level sales share can be found in the online appendix.

[11] In the local polynomial regression, we use a tricube kernel and the nearest neighborhood bandwidth with coverage of 0.7, and we set the degree of local polynomial at 2. For further details, see Loader (1999).

[12] Note that these crowdedness measures are not the total number of passengers at each station because the numbers are based on surveys. MLIT considers the Metropolitan Transportation Census as capturing the variation in population and estimates the total passenger size using the multipliers that it developed. The multipliers that the ministry uses to calculate the size of population vary across train operators. The average multipliers across operators is 194.0.

[13] The regression results are available upon request from the authors.

[14] Regarding crowd pressure, customers may feel crowd pressure in various ways, such as pressure that other people in close proximity might be observing the customer's choice and pressure that customers may be physically restricted in a crowded location, causing them to feel distressed.

[15] The price of a product does not change during the sample period. Most products are priced at either 120 or 200 Japanese Yen, depending on the package size. Some seasonal products with special flavors are sold at a higher price than the regular price. Our empirical analysis includes product fixed effects to control for the price effect. For detailed information about the prices and categories, see the online appendix.

[16] If we simply apply the average multiplier used by MLIT, 194.0, these numbers imply that, on average, 26,325.8 passengers pass a station in one hour and 317 passengers pass a station in one minute.

[17] The difference might be statistically significant for some variables, but it is small in magnitude and does not affect our estimates.

[18] We consider both time-of-day (i.e., morning, daytime, and nighttime) and hour fixed effects. Because our results are robust to both specifications, we report the results with hour fixed effects in the online appendix.

[19] Moreover, Imbens (2014) suggests the use of matching estimators when the estimates are sensitive to parametric specification or the covariates are distributed quite differently for the treatment and control groups. In our case, as shown in Table 6, there are no significant differences in the covariates between the treatment and control groups, and as we show in Section 3.5, our main estimates based on Poisson distribution are quantitatively quite close to the estimates based on negative binomial distribution. Hence, we think that the parametric model that we specify does not bias our estimates compared with matching estimators.

[20] The estimation results of Equations (1) and (2) are robust when machine × timing fixed effects are added.

[21] Hence, if a product is recommended, the product's sales increase by 7.5% = 3.84% + 3.64% by summing up the direct effect and the indirect effect.

[22] Note that there are approximately 500 vending machines and 3 different timings, so we added 1,500 more fixed effects.

[23] It is computationally infeasible to estimate the models with machine-product-timing fixed effects. Because there are roughly 500 machines, 100 products, and 3 timings, there would be approximately 150,000 more fixed effects.

[24] To further mitigate the concern for self-selection that consumers who approach vending machines under high time and crowd pressures may be different from average consumers, we regress the pressure measures on the observed characteristics such as age, gender, and the use of commuter cards by the consumers as the covariates, including time and social pressure, as in the machine-level regression. The results imply that the time and crowd pressures are not correlated with these observed characteristics. Although we cannot exclude the possibility that the pressures are correlated with unobserved customer characteristics, the concern for self-selection may be mitigated to the extent that the observed characteristics are informative regarding unobserved characteristics.

[25] Note that there is little cost to change recommendations as the company can easily change recommendations of all machines digitally.

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