

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 non-recommended products, we show that time pressures moderate the effectiveness of product recommendations for both recommended products directly and non-recommended products indirectly. Crowd pressure weakens the direct effect on the recommended products although its impact on the non-recommended 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.

Keywords: Product Recommendation, Time Pressure, Crowd Pressure, Spillover Effect, Context-based Marketing

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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 due to 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 with 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.

Since 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, Dahl, and Manchanda (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 communi-

cation 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 due to endogeneity problems. If a company recommends products based on its (unobserved) popularity, the difference in sales between the recommended and non-recommended 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 non-recommended 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. Since 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. Since our proxy variables for time and crowd pressures vary frequently at the minute level, whereas 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 vend-

ing 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*. Since we include both variables in the model, the coefficient on *machine_PR* captures the indirect effect of making recommendations to non-recommended 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 non-recommended products). A 10% increase in

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

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 Kahneman and Frederick (2002) and Baumeister, Muraven, and Tice (1998)'s finding 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)), while the fact that it is driven by the spillover effect to non-recommended good indicates that product recommendations might not necessarily have conformity effects, as in Asch (1951) and Sherif (1935).

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 non-recommended products on the menu, and the spillover effects can vary by the degree of time pressure and crowd pressure. Second, while 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. While Section 2 reviews the related literature, Section 3 discusses time and crowd pressures. Section 4 explains our experimental design and describe 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, Essegaier, and Kohli (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, Essegaier, and Kohli (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, Hu, and Rahman (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, since 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, Luo, Fang, and Ghose (2015) show that advertisements on crowded trains increase purchase likelihood. Molitor, Reichhart, Spann, and Ghose (2016) show that the distance between consumers and store locations affects the effectiveness of advertisements. Luo, Andrews, Fang, and Phang (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, Dahl, and Manchanda (2005) and Dahl, Argo, and Manchanda (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, Shen, and Wyer (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, Nagel, Camerer, and Rangel (2011) use an eye-tracker to study the consumers'

²Kawaguchi, Uetake, and Watanabe (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.

decision making under time pressure. An exception to the non-laboratory setup to study the effects of crowd and time pressures is Hui, Bradlow, and Fader (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 non-laboratory 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 Effect, Spillover Effect, and Sales Effect

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 non-recommended product, which comprise the overall sales effect at the store-level (or the vending-machine level). While 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 *non-recommended* 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 non-recommended products. We define this spillover effect of recommendations on the consumers' tendency to purchase non-recommended 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., Kawaguchi, Uetake, and Watanabe (2016); Seiler (2013); Zhou (2014)).

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 non-recommended 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, Nagel, Camerer, and Rangel (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 Kahneman and Frederick (2002) and Baumeister, Muraven, and Tice (1998) 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 (Asch (1951); Sherif (1935)) suggest that when consumers are surrounded by other consumers, they decide differently and tend to match their behavior to group norms. Hui, Bradlow, and Fader (2009), for example, find

³Note 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.

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, Hutt, and Anderson (1980) also find that shoppers tend to follow the traffic pattern of other shoppers. In contrast, social impact can also induce avoidance of shopping since some consumers may hesitate to reveal their purchase in public (e.g., Hui and Bateson (1991)). Argo, Dahl, and Manchanda (2005) also find that consumers are less likely to make a purchase if there are too many people around due to 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 to 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

⁴The 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).

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



Figure 1: A vending machine used for the experiment on a train platform: 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.



Figure 2: An image of the touch-panel and product recommendations: The product recommendations are the flashing red bubble signs with the word “Recommended.” The image is supplied by the company.

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

⁶Cameras 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.

⁷Note that consumers can see all of the available products on the display regardless of whether they are recom-

The digital display allows the company to change its recommendations more easily than the traditional vending machines or other retail-shopping settings since 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 am), daytime (between 10 am and 6 pm), and night (after 6 pm). For example, a particular brand of coffee is recommended for male consumers in their 40s for the morning. Currently, the set of recommended products for each type of consumers (i.e., gender \times age) is the same across all vending machines since 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.

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 run 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 night) 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 sign “-” indicates that the company runs its regular recommendation system, for which the company (not us) chooses products to recommended or not.

	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
Night	-	T	C	-	T	T	C	-	T	C

Table 1: Experimental design: 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.

ommend. 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 over-estimated. In our case, since 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.

From this experiment, we construct two treatment variables. First, *machine_PR* is a machine-

⁸Note that we have a relatively small number of control groups compared to 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.

⁹The 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 non-recommended products.

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 category¹⁰ 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, while 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*. Since 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 non-recommended 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.

¹⁰The definition of categories is determined by the company. The category-level sales share can be found in Online Appendix.

	Morning	Day	Night
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

Table 2: Number of recommended products in each category for the treatment condition.

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 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.

時間	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	0
到着	32	40	53	2	8	13	17	23	31	33	38	44	45	50	51	53	55	57	58	59	01
出発	33	12	18	27	36	45	54	3	6	8	14	17	19	24	26	29	31	36	38	40	42
到着	3	6	8	14	17	19	24	26	29	31	36	38	40	42	44	46	48	50	52	54	56
出発	1	3	5	7	9	11	13	15	17	19	21	26	28	30	32	34	36	39	41	46	48
到着	1	6	12	16	19	23	26	31	33	38	41	47	49	53	57	58	59	01	02	03	04
出発	5	6	10	17	19	24	32	33	35	37	44	45	50	53	54	55	57	58	59	01	02
到着	0	2	5	7	13	14	23	29	31	36	38	43	45	53	59	01	02	03	04	05	06
出発	0	4	6	13	14	23	29	31	36	38	43	45	53	59	01	02	03	04	05	06	07
到着	0	4	7	13	14	23	30	31	37	38	44	45	53	59	01	02	03	04	05	06	07
出発	0	4	6	13	15	21	22	31	36	38	43	45	53	59	01	02	03	04	05	06	07
到着	0	4	6	13	15	23	30	31	36	38	43	44	53	59	01	02	03	04	05	06	07
出発	0	4	11	12	16	22	27	29	31	35	37	39	42	46	51	53	55	58	59	01	02
到着	1	5	6	11	13	15	18	21	24	28	30	32	36	37	40	43	46	48	52	54	58
出発	3	5	8	11	16	20	24	27	30	34	36	38	41	45	49	53	54	58	59	01	02
到着	3	6	8	12	16	22	27	30	34	36	38	41	44	48	53	57	58	59	01	02	03
出発	0	3	7	10	13	18	21	24	29	35	37	40	42	47	55	59	01	02	03	04	05
到着	1	5	7	13	14	19	26	29	31	35	36	41	47	53	57	58	59	01	02	03	04
出発	3	4	7	12	15	17	25	31	31	36	37	40	43	47	49	53	59	01	02	03	04
到着	0	4	10	13	18	22	26	29	33	40	45	49	58	59	01	02	03	04	05	06	07
出発	0	15	36	47																	

Figure 3: A sample train timetable. Train frequency differs significantly by hour. The figure provides the weekday train timetable of Chuo Line at Mitaka Station. The image is prepared by the authors.

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. 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 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. Since *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 pres-

¹¹In 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).

¹²Note 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.



Figure 4: Railway platforms where vending machines are placed. 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 is prepared by Hiromi Watanabe and that on the right is from Wikipedia <https://en.wikipedia.org/wiki/Rush-hour>

sures 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 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 \times 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. Based on 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 Online Appendix.

Moreover, some confounding factors cannot be ruled out because the variations in time and crowd pressure measures are non-experimental. 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 crowd 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.

Lastly, we cannot separately identify the different psychological theories leading to time

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

	Mean	Std. Dev	Min	Max
No. of Machines	2.46	3.03	1	30
Average Temperature (Celcius)	25.97	1.56	20	29
Average Precipitation (mm)	3.98	2.65	0	12.15

Table 3: Summary statistics for stations.

	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
Night	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

Table 4: Summary statistics for vending machines.

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 degrees Celsius, 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 rev-

¹⁴Regarding 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.

enue of approximately 20,000 Japanese yen (\$200 US dollars).¹⁵ On average, the daytime sales (74 bottles/cans) are greater than the morning and night sales, but this is mainly because the daytime (8 hours) is longer than the morning (5 hours) and night (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.

		Obs	mean	sd	min	max
All	time to next	1944970	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	586170	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	782400	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
Evening	time to next	576400	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

Table 5: Summary statistics for the number of passengers and time to the next train

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 evening 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

¹⁵The 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 Online Appendix.

¹⁶If 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.

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.

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.

	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

Table 6: Balance check

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

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



Figure 5: Average effects of recommendations on machine-level sales. Note: 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.

Graphical Evidence of ATE 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 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.

$$\log E(sales_{kt} | machine_PR_{kt}, x_{kt}, \mu) = \alpha \times machine_PR_{kt} + x'_{kt} \beta + \mu_t + \mu_k + \mu_d, \quad (5.1)$$

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. 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-vending 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:

$$\begin{aligned} & \log E(\text{sales}_{ikt} | \text{product_PR}_{ikt}, \text{machine_PR}_{kt}, x_{kt}, \mu) \\ &= \alpha_1 \text{product_PR}_{ikt} + \alpha_2 \text{machine_PR}_{kt} + x'_{kt} \beta + \mu_i + \mu_k + \mu_t + \mu_d, \end{aligned} \quad (5.2)$$

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). machine_PR_{kt} is similarly defined as equation (5.1), 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

¹⁸We consider both time-of-day (i.e., morning, daytime and night) and hour fixed effects. Since our results are robust to both specifications, we report the results with hour fixed effects in Online Appendix.

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 (5.1). Model (1) includes the time fixed effect (i.e., morning, daytime, and night) 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 (5.2). 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 non-recommended products; the spillover effect is positive. Recommendations increase the sales of the recommended products by 3.84% through the choice effect, which does not

¹⁹Moreover, 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 to matching estimators.

²⁰The estimation results of equations (5.1) and (5.2) are robust when machine \times timing fixed effects are added.

account for the spillover effect, and the sales of the non-recommended 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.

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

Table 7: Machine-level Poisson Regression Results

Note: Standard errors are in parentheses and are clustered at the machine level. Both models contain machine and day fixed effects. Model (1) includes time fixed effect in addition, and Model (2) includes hour fixed effect.

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

Table 8: Product-level Poisson Regression Results

Standard errors are in parentheses and are clustered at the machine level. Both models contain machine and day fixed effects. Model (1) includes the time fixed effect in addition, and Model (2) include the hour fixed effect.

²¹Hence, 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.

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:

$$\begin{aligned}
 & \log E(\text{sales}_{kt} | D_{kt}, \text{time}_{kt}, \text{crowd}_{kt}, x_{kt}, \mu) \\
 = & \alpha_1 \times \text{machine_PR}_{kt} \\
 & + \alpha_2 \times (\text{machine_PR}_{kt} \times \text{time}_{kt}) + \alpha_3 \times (\text{machine_PR}_{kt} \times \text{crowd}_{kt}) \\
 & + \alpha_4 \times \text{time}_{kt} + \alpha_5 \times \text{crowd}_{kt} + x'_{kt} \beta + \mu_k + \mu_d + \mu_t.
 \end{aligned} \tag{5.3}$$

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}*. Since we have three different variables to measure time and crowd pressures, respectively, we try all combinations of these: *time* $\in \{\textit{departure}, \textit{departure_next1}, \{\textit{time_to_next}, \textit{time_after_next}\}\}$ and *crowd* $\in \{\textit{crowdedness_hour}, \textit{crowdedness_minute_1}, \textit{crowdedness_minute_2}\}$. 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 night). Finally, as in the previous section, we cluster the standard errors at the vending machine level.

Table 9 reports the estimation results for equation (5.3) 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 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

	(1)	(2)	(3)
temperature	0.0792*** (0.00315)	0.0792*** (0.00315)	0.0785*** (0.00318)
precipitation	-0.00186*** (0.000371)	-0.00189*** (0.000372)	-0.00203*** (0.000376)
machine_PR	0.0668*** (0.00504)	0.0660*** (0.00519)	0.00345 (0.00682)
crowdedness_hour	0.000159*** (0.0000117)	0.000154*** (0.0000117)	0.0000873*** (0.0000110)
departure	0.204*** (0.0101)		
machine_PR × crowdedness_hour	0.0000158*** (0.00000307)	0.0000146*** (0.00000318)	0.00000976** (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*** (0.0864)	-3.829*** (0.0862)	-2.942*** (0.0879)
Observations	3,399,480	3,399,480	3,146,045

Table 9: Machine-level Poisson Regression Results with Hour Crowdedness

Standard errors are reported in parentheses and clustered at the machine level. Machine, day, and time fixed effects are controlled for.

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 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, while 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

	(1)	(2)	(3)
temperature	0.0784*** (0.00298)	0.0784*** (0.00298)	0.0771*** (0.00304)
precipitation	-0.00276*** (0.000363)	-0.00276*** (0.000364)	-0.00284*** (0.000372)
machine_PR	0.0734*** (0.00499)	0.0724*** (0.00508)	0.00807 (0.00626)
crowdedness_hour	0.000259*** (0.0000169)	0.000250*** (0.0000166)	0.000156*** (0.0000134)
departure	0.179*** (0.00951)		
machine_PR × crowdedness_hour	-0.00000237 (0.00000320)	-0.00000329 (0.00000337)	-0.00000656 (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*** (0.0764)	-3.886*** (0.0762)	-3.010*** (0.0794)
Observations	3399480	3399480	3146045

Table 10: Poisson Regression Results: Machine-Level, Hour Crowdedness, More Fixed Effects: Standard errors are clustered at the machine level and reported in parentheses. Day fixed effects and machine x timing fixed effects are controlled.

* : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$

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 A.5 and A.6, respectively in 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.

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 (5.2), we run the following Poisson model:

$$\begin{aligned}
 & \log E(\text{sales}_{ikt} | \text{product}_{ikt}, \text{machine_PR}_{kt}, \text{time}_{kt}, \text{crowd}_{kt}, x_{kt}, \mu) & (5.4) \\
 = & \alpha_1 \text{product_PR}_{ikt} + \alpha_2 \text{machine_PR}_{kt} \\
 & + \alpha_3 (\text{product_PR}_{ikt} \times \text{time}_{kt}) + \alpha_4 (\text{product_PR}_{ikt} \times \text{crowd}_{kt}) \\
 & + \alpha_5 (\text{machine_PR}_{kt} \times \text{time}_{kt}) + \alpha_6 (\text{machine_PR}_{kt} \times \text{crowd}_{kt}) + \alpha_7 \times \text{time}_{kt} + \alpha_8 \times \text{crowd}_{kt} \\
 & + x'_{kt} \beta + \mu_i + \mu_k + \mu_d + \mu_t,
 \end{aligned}$$

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

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

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 non-recommended products.

Table 11 presents the estimation results of equation (5.4) for *crowdedness_hour*, and Tables A.7 and A.8 in 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.

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-timing and machine-timing fixed effects.²³ In Section 5.2,

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

	(1)	(2)	(3)
temperature	0.0797*** (0.00306)	0.0797*** (0.00306)	0.0797*** (0.00334)
precipitation	-0.00156*** (0.000351)	-0.00156*** (0.000351)	-0.00208*** (0.000415)
crowdedness_hour	0.000156*** (0.0000123)	0.000156*** (0.0000123)	0.0000875*** (0.0000116)
machine_PR	0.0494*** (0.00494)	0.0482*** (0.00499)	0.0224*** (0.00559)
product_PR	0.0801*** (0.0113)	0.0793*** (0.0112)	0.0546*** (0.0129)
departure	0.196*** (0.0120)		
machine_PR × crowdedness_hour	0.0000270*** (0.00000309)	0.0000264*** (0.00000307)	0.0000179*** (0.00000337)
product_PR × crowdedness_hour	-0.0000684*** (0.00000871)	-0.0000687*** (0.00000871)	-0.0000647*** (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*** (0.105)	-7.441*** (0.105)	-7.176*** (0.115)
Observations	108188100	108188100	81508362

Table 11: Product-level Poisson Regression with Hour Crowdedness

Note: Standard errors are reported in parentheses and are clustered at the machine level.

we find that the coefficients of the machine-level regression are robust to adding machine-timing fixed effects except for the coefficient on $machine_PR \times crowdedness_hour$. Here, we examine whether there is a similar pattern in the product-level regression.

Table A.10 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 Online Appendix. We find that the results on time pressures remain unchanged to the introduction of machine-timing fixed effects and product-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 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 A.11 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 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. While the details of the robustness checks can be found in Online Appendix, 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 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

²⁴To 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 ob-

	(1)	(2)	(3)
temperature	0.0791*** (0.00289)	0.0791*** (0.00289)	0.0795*** (0.00315)
precipitation	-0.00245*** (0.000344)	-0.00245*** (0.000344)	-0.00316*** (0.000409)
crowdedness_hour	0.000261*** (0.0000172)	0.000261*** (0.0000172)	0.000179*** (0.0000145)
machine_PR	0.0574*** (0.00498)	0.0577*** (0.00499)	0.0287*** (0.00547)
product_PR	0.0651*** (0.0109)	0.0645*** (0.0109)	0.0484*** (0.0126)
departure	0.169*** (0.0114)		
machine_PR × crowdedness_hour	0.00000431 (0.00000342)	0.00000446 (0.00000343)	-0.00000515 (0.00000365)
product_PR × crowdedness_hour	-0.0000306** (0.00000963)	-0.0000308** (0.00000962)	-0.0000236* (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*** (0.0970)	-7.516*** (0.0970)	-7.181*** (0.107)
Observations	108188100	108188100	81508353

Table 12: Product-level Poisson Regression Results with Hour Crowdedness and Machine x Timing Fixed Effects

	(1)	(2)	(3)
temperature	0.0794*** (0.00304)	0.0794*** (0.00304)	0.0795*** (0.00327)
precipitation	-0.00157*** (0.000346)	-0.00157*** (0.000346)	-0.00209*** (0.000404)
crowdedness_hour	0.000157*** (0.0000122)	0.000157*** (0.0000123)	0.0000892*** (0.0000116)
machine_PR	0.0437*** (0.00495)	0.0440*** (0.00495)	0.0191*** (0.00561)
product_PR	0.139*** (0.0117)	0.139*** (0.0117)	0.0957*** (0.0132)
departure	0.195*** (0.0120)		
machine_PR × crowdedness_hour	0.0000202*** (0.00000315)	0.0000204*** (0.00000317)	0.0000114*** (0.00000345)
product_PR × crowdedness_hour	-0.0000251** (0.00000893)	-0.0000254** (0.00000894)	-0.0000209* (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*** (0.171)	-7.941*** (0.171)	-7.744*** (0.166)
Observations	108188100	108188100	81508353

Table 13: Produce-level Poisson Regression with Hour Crowdedness and Product × Timing Fixed Effects

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 non-recommended 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 non-recommended 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 Dhar and Nowlis (1999)'s 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 Kahneman and Frederick (2002)'s findings that people tend to engage in heuristic decision making under time pressure, in that the simplest heuristic decision,

served 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.

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

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 non-recommended 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 non-recommended 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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A Online Appendix (not for publication)

A.1 More Details on the Background Information

In this section, we report some details on price and category-level market shares.

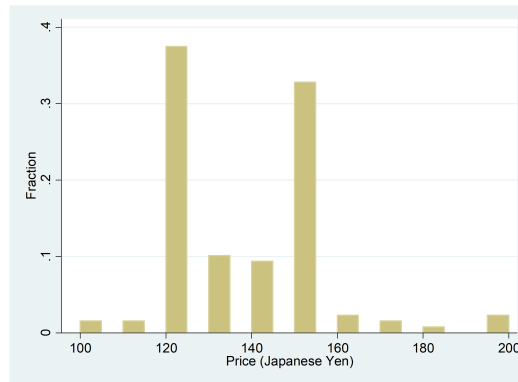


Figure A.1: Distribution of Price: The graph shows the distribution of price of a beverage. The unit is Japanese yen (approximately, \$1 = 100 yen).

Figure A.1 shows the price distribution of all available products. The prices of all products remain unchanged through the sample period. The price distribution ranges from 100 to 200 Japanese yen, but approximately 70% of products are priced at either 120 or 150 Japanese yen. Beverages in a small can (350 *ml*) are typically sold at 120 Japanese yen, whereas those in a large plastic bottle (500 *ml*) are sold at 150 Japanese yen. Some seasonal beverages with special flavor or taste are sold at a higher price than that of regular products, such as 200 Japanese yen. Figure A.1 illustrates limited price variation across products, indicating that the price of most products are determined by package size.

Figure A.2 reports market shares by category. The company categorizes each product into 1 of 11 categories. This distribution in our sample is similar to that of the entire beverage industry, including other channels such as supermarkets and convenience stores.²⁶ Hence,

²⁶The market shares in the Japanese beverage industry by categories are as follows: soda (18%), tea (28%), water (14%), and coffee (15%). See the following website for details, http://www.ccwest.co.jp/pdf/ir/annualreview/ccw/an_2012_06.pdf

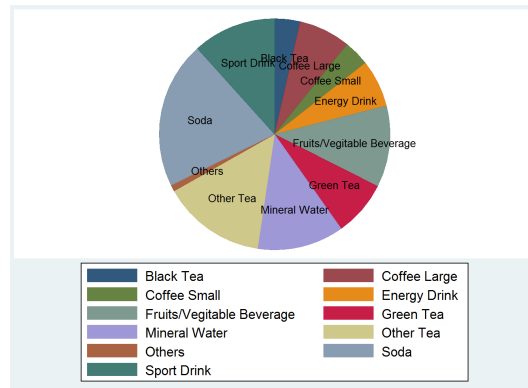


Figure A.2: Market Share by the Types of Drink.

the consumer preference in our sample (i.e., customers who purchase from particular types of vending machines) might not differ significantly from that in the overall beverage market.

A.2 Validity Check

In this section, we present the validity check for the variables used in our estimation, which we intend to capture the time and crowd pressures that consumers may experience when making purchase decisions in front of vending machine. Since time and crowd pressures are not directly observed in the data, we use the time until the next train's arrival as a main proxy for time pressure and number of passengers on the platform as proxy for crowd pressure. The validity check is to show that these proxies are meaningful for the purpose of this study.

Our validity checks follow the standard procedure used in the behavioral psychology literature. We conducted a series of experiments, where the subjects are expected to purchase beverages, as we will explain below. At the time of purchase, subjects respond to the survey question asking how they felt about the time and crowd pressures.

We first investigate our proxy variable for time pressure. We are interested in whether the time to the next train arrival correlates with the extent of the subjects' time pressure. For this, we recruited 29 undergraduate students from Hitotsubashi University in Tokyo. The experiment was conducted as follows (Online Appendix B provides the instructions and survey ques-

tionnaire given to the subjects):

1. The subjects were instructed to take a train from a particular station and to return to the station by taking a particular route, (which we call a trip hereafter). The subjects received a monetary payment that decreased as the time passed until they came back to the university.
2. During a trip, a subject was asked to purchase one beverage from each of three vending machines placed at three different stations on the route that each subject was instructed to take. These vending machines were the ones used in our main experiment. When each subject purchased a beverage, he/she was asked to record the time to the next train arrival; this was displayed on a board in the platform.
3. Each subject was also asked to complete a small task, such as to take a photo of every station during the trip. The purpose of assigning such small tasks is to ensure that the subjects took the route as instructed.
4. Once the subject returned to the university, he/she answered the survey questions, where they rated the degree of time pressure they felt.

We also confirm the validity of our proxy variable for crowd pressure. As in the previous experiment, we recruited 52 undergraduate students of Hitotsubashi University. The experiment was conducted as follows.

1. A subject was instructed to take a train from a particular station and to return by taking a particular route. The subjects traveled to these vending machines in groups of two, three, and four.
2. During the trip, each subject was asked to purchase one beverage from each of three vending machines placed at three different stations on the route that each subject was instructed. Those vending machines were also used in our main experiment. When each

subject purchased a beverage, he/she was asked to record the number of people around at the time of purchase.

3. Each subject was also asked to complete a small task such as to take a photo of every station during the trip. The purpose of assigning such small tasks was to ensure that the subjects took the route as instructed.
4. Once the subject returned to the university, he/she was instructed to provide their observations on how other subjects made their choices. They also answered the survey questions on the degree of their care about the people around them when making purchases.

Table A.1 reports the summary statistics of the subjects' answers to the survey questions Q1–Q4 and on two measures that we use as proxies for time and crowd pressures, respectively. We drop the observations with missing values from our analysis to have 86 observations in the first validity experiment and 144 in the second. Note that each subject made multiple purchases. On average, the subjects had to wait about three minutes until the next train arrived. The average degree of time pressure they felt was 5.36 out of 10 for the first question and 3.35 out of 5 for the second question, but they vary significantly by subject. As for crowd pressure, there were about 8 people around the subjects when they made a purchase and the average degree of crowd pressure was 3.92 out of 5 for the third question and 1.80 out of 10 for the fourth question, but again they varied significantly by subject.

In order to see whether the time to the next train works as a proxy for time pressure, we regress the recorded responses of subjects to Q1 and Q2 on the time to the next train. Similarly, in order to examine whether the number of people around would be a good proxy for pressure from the existence of other people around, we regress the recorded responses to Q3 and Q4 on the number of people around subjects at the time of purchase. We also include individual fixed effect in the regression.²⁷

²⁷The raw correlation between Q3, Q4 and the time pressure measure are 0.25 and 0.20 (both statistically significant), respectively.

	Obs	Mean	Std. Dev	Min	Max
Time to next train	86	3.23	2.33	0	11
Q1	86	5.36	3.05	0	10
Q2	86	3.35	1.37	1	5
# of people around	144	7.61	6.12	1	30
Q3	144	3.92	1.05	1	5
Q4	144	1.80	1.89	0	8

Table A.1: Summary Statistics for the Variables Used in Validity Check.

The following table reports the regression results. The first two columns report the results of the validity check for time pressure. For both questions, the coefficient on the time to next train is negative and statistically significant at the 1% level. Thus, the subject experienced more time pressure from the shorter time to the next train. The third and fourth columns report the results of the validity check for crowd pressure. For both questions, the coefficients are positive and statistically significant at the 1% level. Thus, the subjects felt more pressure from the presence of others when more people are around.

	Q1	Q2	Q3	Q4
Time to next	-0.75*** (-6.01)	-0.29*** (-5.01)		
# of people around			0.11*** (4.22)	0.06*** (3.66)
Constant	6.15*** (4.66)	4.58*** (7.38)	3.94*** (5.42)	3.06*** (6.65)
Individual FE	Yes	Yes	Yes	Yes
Observations	86	86	144	144
R^2	0.642	0.609	0.721	0.633

Table A.2: Regression Results on Validity Checks: t statistics are reported in parentheses. *** indicates statistical significance at 1% level.

In sum, the two experiments we conducted indicate that the time to the next train and number of people around at the time of purchase would be good proxy variables for time pres-

sure and crowd pressure, which we investigate in our main analysis.

A.3 More Results

In this section, we report the estimation results that we omit in the main text. Tables A.3 and A.4 show the estimation results of the machine-level regression of equation (5.3) in which we use *crowdedness_minute_1* and *crowdedness_minute_2* for the crowdedness measure. We find that the coefficients on *machine_PR* × *crowdedness_minute_1* and *machine_PR* × *crowdedness_minute_2* are mostly positive as in the main text. Hence, crowd pressure tends to moderate the effectiveness of product recommendation.

Next, Tables A.5 and A.6 report the results for the machine-level regression with more fixed effects. The model is the same as equation (5.3), but μ_{kt} (instead of μ_k and μ_t) is included. With machine x timing fixed effects, the sign of the coefficients on *machine_PR* × *crowdedness* switched from positive to negative as we find in the main text with *crowdedness_hour* for the crowdedness measure.

Now, we report the product-level analysis results that we omit in the main text. First, Tables A.7 and A.8 report the results of the product-level regression model in equation (5.4) with *crowdedness_minute_1* and *crowdedness_minute_2* for the crowdedness measure. The results are consistent with Table 11 in the main text. We find that crowd pressure increases the choice effect of recommendations, while attenuates the spillover effect of recommendations.

Lastly, Tables report the estimation results of equation (5.4) with more fixed effects. The estimation results are reported in Tables A.11 and A.12. The estimated coefficients indicate that our results are robust to adding product x timing fixed effects.

A.4 Robustness Checks

In this section we report the results of the robustness checks we discussed in Section 5.

	(1)	(2)	(3)
temperature	0.0795*** (0.00315)	0.0795*** (0.00316)	0.0787*** (0.00318)
precipitation	-0.00203*** (0.000372)	-0.00205*** (0.000373)	-0.00213*** (0.000377)
machine_PR	0.0732*** (0.00508)	0.0722*** (0.00524)	0.00777 (0.00647)
crowdedness_minute_1	0.00754*** (0.000465)	0.00740*** (0.000464)	0.00491*** (0.000432)
departure	0.220*** (0.0106)		
machine_PR × crowdedness_minute_1	0.000389* (0.000169)	0.000336* (0.000170)	0.0000968 (0.000200)
machine_PR × departure	-0.0678*** (0.00675)		
departure_next1		0.286*** (0.00964)	
machine_PR × departure_next1		-0.0632*** (0.00734)	
time to next			-0.0831*** (0.00250)
time to after next			-0.0595*** (0.00284)
machine_PR × time to next			0.0126*** (0.00142)
machine_PR × time to after next			0.00245 (0.00138)
Constant	-3.797*** (0.0860)	-3.808*** (0.0859)	-2.923*** (0.0870)
Observations	3399480	3399480	3146045

Table A.3: Poisson Regression Results: Machine Level, Minute Crowdedness: Standard errors are in parentheses. The standard errors are machine-level cluster robust. Machine, day, and time fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0789*** (0.00316)	0.0790*** (0.00316)	0.0783*** (0.00319)
precipitation	-0.00187*** (0.000371)	-0.00190*** (0.000371)	-0.00205*** (0.000375)
machine_PR	0.0651*** (0.00511)	0.0645*** (0.00526)	-0.00134 (0.00704)
crowdedness_minute_2	0.0163*** (0.00149)	0.0156*** (0.00149)	0.00700*** (0.00141)
departure	0.198*** (0.00962)		
machine_PR × crowdedness_minute_2	0.00154*** (0.000270)	0.00142*** (0.000268)	0.00102*** (0.000289)
machine_PR × departure	-0.0669*** (0.00688)		
departure_next1		0.263*** (0.00904)	
machine_PR × departure_next1		-0.0623*** (0.00739)	
time to next			-0.0825*** (0.00251)
time to after next			-0.0592*** (0.00284)
machine_PR × time to next			0.0131*** (0.00142)
machine_PR × time to after next			0.00309* (0.00141)
Constant	-3.843*** (0.0873)	-3.851*** (0.0871)	-2.939*** (0.0891)
Observations	3399480	3399480	3146045

Table A.4: Poisson Regression Results: Machine Level, Smoothed Minute Crowdedness: Standard errors are reported in parentheses and clustered at the machine level. Machine, day, and time fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0783*** (0.00297)	0.0784*** (0.00298)	0.0770*** (0.00304)
precipitation	-0.00275*** (0.000362)	-0.00275*** (0.000362)	-0.00284*** (0.000371)
machine_PR	0.0765*** (0.00499)	0.0757*** (0.00511)	0.00665 (0.00586)
crowdedness_minute_1	0.00939*** (0.000514)	0.00925*** (0.000512)	0.00643*** (0.000434)
departure	0.212*** (0.0102)		
machine_PR × crowdedness_minute_1	-0.000180 (0.000169)	-0.000236 (0.000172)	-0.000553** (0.000205)
machine_PR × departure	-0.0724*** (0.00616)		
departure_next1		0.281*** (0.00927)	
machine_PR × departure_next1		-0.0679*** (0.00666)	
time to next			-0.0825*** (0.00246)
time to after next			-0.0602*** (0.00265)
machine_PR × time to next			0.0127*** (0.00134)
machine_PR × time to after next			0.00331* (0.00130)
Constant	-3.835*** (0.0765)	-3.851*** (0.0763)	-2.956*** (0.0789)
Observations	3399480	3399480	3146045

Table A.5: Poisson Regression Results: Machine-Level, Minute Crowdedness, Machine x Timing FE: Standard errors are in parentheses and clustered at the machine level. Day-of-week and machine x timing fixed effects are included.

	(1)	(2)	(3)
temperature	0.0784*** (0.00299)	0.0785*** (0.00299)	0.0771*** (0.00305)
precipitation	-0.00279*** (0.000364)	-0.00279*** (0.000364)	-0.00284*** (0.000371)
machine_PR	0.0741*** (0.00504)	0.0732*** (0.00512)	0.0119 (0.00665)
crowdedness_minute_2	0.0308*** (0.00227)	0.0297*** (0.00223)	0.0172*** (0.00186)
departure	0.158*** (0.00886)		
machine_PR × crowdedness_minute_2	-0.000877** (0.000307)	-0.000928** (0.000312)	-0.000783* (0.000313)
machine_PR × departure	-0.0567*** (0.00651)		
departure_next1		0.225*** (0.00852)	
machine_PR × departure_next1		-0.0524*** (0.00700)	
time to next			-0.0791*** (0.00234)
time to after next			-0.0571*** (0.00253)
machine_PR × time to next			0.0120*** (0.00133)
machine_PR × time to after next			0.00278* (0.00131)
Constant	-3.949*** (0.0775)	-3.959*** (0.0774)	-3.068*** (0.0811)
Observations	3399480	3399480	3146045

Table A.6: Poisson Regression Results: Machine-Level, Smoothed Miniute Crowdedness, Machine x timing Fixed Effects: Standard errors are in parentheses and are clustered at the machine level. Day-of-week and machine x timing fixed effects are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1)	(2)	(3)
temperature	0.0802*** (0.00306)	0.0802*** (0.00306)	0.0802*** (0.00330)
precipitation	-0.00172*** (0.000353)	-0.00172*** (0.000353)	-0.00218*** (0.000411)
crowdedness_minute_1	0.00749*** (0.000471)	0.00748*** (0.000471)	0.00497*** (0.000447)
machine_PR	0.0566*** (0.00494)	0.0570*** (0.00496)	0.0303*** (0.00539)
product_PR	0.0716*** (0.0109)	0.0710*** (0.0109)	0.0328** (0.0120)
departure	0.211*** (0.0131)		
machine_PR × crowdedness_minute_1	0.000839*** (0.000170)	0.000845*** (0.000171)	0.000448* (0.000201)
product_PR × crowdedness_minute_1	-0.00273*** (0.000426)	-0.00275*** (0.000427)	-0.00281*** (0.000508)
machine_PR × departure	-0.0503*** (0.00655)		
product_PR × departure	-0.0487*** (0.0132)		
departure_next1		0.214*** (0.0131)	
machine_PR × departure_next1		-0.0511*** (0.00652)	
product_PR × departure_next1		-0.0472*** (0.0134)	
time to next			-0.000740*** (0.000200)
time to after next			0.0000588 (0.000630)
machine_PR × time to next			0.000335* (0.000157)
machine_PR × time to after next			-0.000328 (0.000903)
product_PR × time to next			0.000922*** (0.000278)
product_PR × time to after next			0.000177 (0.00171)
Constant	-7.422*** (0.105)	-7.422*** (0.105)	-7.181*** (0.113)
Observations	108188100	108188100	81508353

Table A.7: Poisson Regression Results: Product-Level, Minute Crowdedness: Standard errors are in parentheses and clustered at the machine level. The standard errors are machine-level cluster robust. The machine, day-of-week, and time-of-week fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0794*** (0.00307)	0.0794*** (0.00307)	0.0794*** (0.00334)
precipitation	-0.00158*** (0.000351)	-0.00158*** (0.000351)	-0.00211*** (0.000414)
crowdedness_minute_2	0.0154*** (0.00172)	0.0154*** (0.00172)	0.00672*** (0.00155)
machine_PR	0.0476*** (0.00505)	0.0464*** (0.00509)	0.0176*** (0.00585)
product_PR	0.0834*** (0.0115)	0.0827*** (0.0115)	0.0577*** (0.0141)
departure	0.191*** (0.0112)		
machine_PR × crowdedness_minute_2	0.00243*** (0.000313)	0.00238*** (0.000311)	0.00167*** (0.000321)
product_PR × crowdedness_minute_2	-0.00530*** (0.000896)	-0.00533*** (0.000897)	-0.00487*** (0.000961)
machine PR × departure	-0.0533*** (0.00673)		
product PR × departure	-0.0358** (0.0139)		
departure_next1		0.190*** (0.0112)	
machine PR × departure within 1		-0.0499*** (0.00685)	
product PR × departure within 1		-0.0337* (0.0138)	
time to next			-0.000783*** (0.000195)
time to after next			-0.00122 (0.000673)
machine_PR × time to next			0.000439** (0.000161)
machine_PR × time to after next			0.000941 (0.000801)
product_PR=1 × time to next			0.000637* (0.000299)
product_PR=1 × time to after next			-0.00168 (0.00155)
Constant	-7.460*** (0.106)	-7.459*** (0.106)	-7.169*** (0.116)
Observations	108188100	108188100	81508362

Table A.8: Poisson Regression Results: Product-Level, Smoothed Minute Crowdedness: Standard errors are reported in parentheses and clustered at the machine level.

	(1)	(2)	(3)
temperature	0.0790*** (0.00289)	0.0790*** (0.00289)	0.0794*** (0.00314)
precipitation	-0.00245*** (0.000343)	-0.00245*** (0.000343)	-0.00315*** (0.000408)
size_passenger_m	0.00949*** (0.000500)	0.00948*** (0.000500)	0.00714*** (0.000449)
machine_PR	0.0609*** (0.00498)	0.0613*** (0.00499)	0.0276*** (0.00520)
product_PR	0.0610*** (0.0106)	0.0604*** (0.0106)	0.0409*** (0.0114)
departure	0.202*** (0.0131)		
machine_PR=1 × size_passenger_m	0.000127 (0.000178)	0.000133 (0.000178)	-0.000437* (0.000207)
product_PR=1 × size_passenger_m	-0.00125** (0.000416)	-0.00127** (0.000417)	-0.000959* (0.000478)
tre_B_departure	-0.0583*** (0.00626)		
osusume_B_departure	-0.0229 (0.0133)		
departure_within1		0.205*** (0.0130)	
tre_B_departure_next1		-0.0592*** (0.00621)	
osusume_B_departure_next1		-0.0214 (0.0134)	
time to next			-0.000511** (0.000190)
time to after next			-0.00000369 (0.000625)
machine_PR=1 × time to next			0.000572*** (0.000150)
machine_PR=1 × time to after next			-0.000295 (0.000904)
product_PR=1 × time to next			0.000410 (0.000280)
product_PR=1 × time to after next			0.0000261 (0.00171)
Constant	-7.479*** (0.0969)	-7.479*** (0.0969)	-7.131*** (0.106)
Observations	108188100	108188100	81508353

Table A.9: Poisson Regression Results: Product-Level, Minute Crowdedness, Machine x Timing Fixed Effects: Standard errors are in parentheses and clustered at machine level. Day-of-week, product, and machine x timing fixed effects are included.

	(1)	(2)	(3)
temperature	0.0791*** (0.00290)	0.0791*** (0.00290)	0.0795*** (0.00316)
precipitation	-0.00249*** (0.000345)	-0.00248*** (0.000345)	-0.00316*** (0.000409)
crowdedness_SMOOTH	0.0302*** (0.00263)	0.0302*** (0.00262)	0.0197*** (0.00214)
machine_PR	0.0584*** (0.00506)	0.0588*** (0.00506)	0.0344*** (0.00591)
product_PR	0.0629*** (0.0112)	0.0623*** (0.0111)	0.0397** (0.0137)
departure	0.148*** (0.0100)		
machine_PR=1 × crowdedness_SMOOTH	-0.000506 (0.000340)	-0.000490 (0.000342)	-0.000974** (0.000351)
product_PR=1 × crowdedness_SMOOTH	-0.00110 (0.000939)	-0.00112 (0.000938)	-0.000714 (0.000980)
tre_B_departure	-0.0442*** (0.00660)		
osusume_B_departure	-0.0256 (0.0140)		
departure_within1		0.150*** (0.0100)	
tre_B_departure_next1		-0.0452*** (0.00657)	
osusume_B_departure_next1		-0.0240 (0.0140)	
time to next			-0.000119 (0.000174)
time to after next			0.000287 (0.000622)
machine_PR=1 × time to next			0.000433** (0.000153)
machine_PR=1 × time to after next			-0.000371 (0.000905)
product_PR=1 × time to next			0.000462 (0.000288)
product_PR=1 × time to after next			0.0000280 (0.00172)
Constant	-7.588*** (0.0987)	-7.588*** (0.0987)	-7.240*** (0.108)
Observations	108188100	108188100	81508353

Table A.10: Poisson Regression Results: Product-Level, Smoothed Minute Crowdedness, Machine x Timing Fixed Effects: Standard errors are in parentheses and clustered at machine level. Day-of-week, product, and machine x timing fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0794*** (0.00304)	0.0794*** (0.00304)	0.0795*** (0.00327)
precipitation	-0.00157*** (0.000346)	-0.00157*** (0.000346)	-0.00209*** (0.000404)
crowdedness_hour	0.000157*** (0.0000122)	0.000157*** (0.0000123)	0.0000892*** (0.0000116)
machine_PR	0.0437*** (0.00495)	0.0440*** (0.00495)	0.0191*** (0.00561)
product_PR	0.139*** (0.0117)	0.139*** (0.0117)	0.0957*** (0.0132)
departure	0.195*** (0.0120)		
machine_PR × crowdedness_hour	0.0000202*** (0.00000315)	0.0000204*** (0.00000317)	0.0000114*** (0.00000345)
product_PR × crowdedness_hour	-0.0000251** (0.00000893)	-0.0000254** (0.00000894)	-0.0000209* (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*** (0.171)	-7.941*** (0.171)	-7.744*** (0.166)
Observations	108188100	108188100	81508353

Table A.11: Produce-level Poisson Regression with Hour Crowdedness and Product × Timing Fixed Effects

	(1)	(2)	(3)
temperature	0.0791*** (0.00304)	0.0791*** (0.00304)	0.0792*** (0.00327)
precipitation	-0.00158*** (0.000346)	-0.00158*** (0.000346)	-0.00212*** (0.000402)
crowdedness_minute_2	0.0156*** (0.00171)	0.0155*** (0.00171)	0.00687*** (0.00154)
machine_PR	0.0420*** (0.00505)	0.0424*** (0.00505)	0.0147* (0.00587)
product_PR	0.141*** (0.0119)	0.141*** (0.0119)	0.0967*** (0.0143)
departure	0.191*** (0.0112)		
machine_PR × crowdedness_minute_2	0.00190*** (0.000312)	0.00192*** (0.000313)	0.00118*** (0.000326)
product_PR × crowdedness_minute_2	-0.00204* (0.000877)	-0.00207* (0.000875)	-0.00162 (0.000954)
machine_PR × departure	-0.0512*** (0.00674)		
product_PR × departure	-0.0545*** (0.0142)		
departure_within1		0.193*** (0.0112)	
machine_PR × departure_next1		-0.0521*** (0.00672)	
product_PR × departure_next1		-0.0529*** (0.0143)	
time to next			-0.000769*** (0.000194)
time to after next			0.0000427 (0.000627)
machine_PR × time to next			0.000444** (0.000156)
machine_PR × time to after next			-0.000250 (0.000904)
product_PR × time to next			0.000980*** (0.000286)
product_PR × time to after next			0.000138 (0.00170)
Constant	-7.968*** (0.172)	-7.969*** (0.172)	-7.743*** (0.166)
Observations	108188100	108188100	81508353

Table A.12: Poisson Regression Results: Product-Level, Smoothed Minute Crowdedness, Product x Timing Fixed Effects: Standard errors are in parentheses and clustered at machine-level. Day-of-week, machine, and product x timing fixed effects are controlled.

A.4.1 Robustness Check 1: Negative Binomial Regression

In the main text, we use Poisson regression to estimate equations (5.2) and (5.4). In this appendix, we report the results using negative binomial regression instead of Poisson regression. Tables A.13, A.14, and A.15 report the results from the machine-level analysis and Tables ??, ??, and ?? report the results from the product-level analysis.

Our results are quantitatively quite similar to the main results in all specifications. Thus, our results are robust to a change in specification of probability distribution. This robustness check even supports our parametric model because, as suggested by (Imbens 2014), more nonparametric approaches such as matching estimators would be more useful when the results are sensitive to model specification.

A.4.2 Robustness Check 2: Membership Information

In this robustness check, we investigate the robustness of our results to unobserved consumer heterogeneity by using detailed consumer demographic information.

Membership Information In our setup, consumers purchase beverages with either cash or debit card. The debit card works as commuter ticket as well, and we observe that more than half of the transactions have been carried out with debit cards. We consider that those who buy a beverage with their debit card are likely to be commuters who may need to rush into trains, while those who use cash for purchasing beverages are more likely to be non-commuters. Also consumers who use cash for buying beverages may have different tastes compared to those who use a debit card.

Tables A.19 and A.20 present the machine-level results, and Tables A.21 and A.22 present the product-level results. In each table, we split the sample into two subgroups based on the fraction of consumers who purchase beverages with debit cards. In order to save space, we do not report the results with *crowdedness_minute_1* as the proxy variable for crowd pressure, but the results are qualitatively similar to our main results.

	(1)	(2)	(3)
temperature	0.0788*** (0.00310)	0.0789*** (0.00310)	0.0783*** (0.00315)
precipitation	-0.00181*** (0.000370)	-0.00184*** (0.000370)	-0.00199*** (0.000375)
machine_PR	0.0662*** (0.00502)	0.0655*** (0.00516)	0.00383 (0.00677)
crowdedness_hour	0.000166*** (0.0000120)	0.000160*** (0.0000120)	0.0000897*** (0.0000112)
departure	0.204*** (0.00995)		
machine_PR × crowdedness_hour	0.0000161*** (0.00000317)	0.0000148*** (0.00000328)	0.00000987*** (0.00000351)
machine_PR × departure	-0.0631*** (0.00677)		
departure_next1		0.269*** (0.00940)	
machine_PR × departure_next1		-0.0587*** (0.00750)	
time to next			-0.0826*** (0.00247)
time to after next			-0.0586*** (0.00280)
machine_PR × time to next			0.0126*** (0.00142)
machine_PR × time to after next			0.00246 (0.00138)
Constant	-3.812*** (0.0850)	-3.823*** (0.0849)	-2.935*** (0.0870)
lnalpha	-0.696*** (0.0432)	-0.711*** (0.0437)	-0.982*** (0.0502)
Observations	3399480	3399480	3146045

Table A.13: Negative Binomial Regression Results: Machine Level, Hour Crowdedness: Standard errors are in parentheses and clustered at machine-level. Machine, day-of-week, and timing fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0790*** (0.00311)	0.0791*** (0.00311)	0.0784*** (0.00315)
precipitation	-0.00198*** (0.000371)	-0.00199*** (0.000371)	-0.00209*** (0.000376)
machine_PR	0.0723*** (0.00504)	0.0713*** (0.00519)	0.00830 (0.00644)
crowdedness_minute_1	0.00814*** (0.000512)	0.00800*** (0.000512)	0.00512*** (0.000458)
departure	0.218*** (0.0104)		
machine_PR × crowdedness_minute_1	0.000371* (0.000179)	0.000308 (0.000181)	0.0000805 (0.000204)
machine_PR × departure	-0.0657*** (0.00675)		
departure_next1		0.285*** (0.00950)	
machine_PR × departure_next1		-0.0612*** (0.00731)	
time to next			-0.0834*** (0.00249)
time to after next			-0.0593*** (0.00282)
machine_PR × time to next			0.0125*** (0.00142)
machine_PR × time to after next			0.00236 (0.00138)
Constant	-3.786*** (0.0847)	-3.798*** (0.0846)	-2.915*** (0.0862)
lnalpha	-0.682*** (0.0429)	-0.699*** (0.0435)	-0.980*** (0.0503)
Observations	3399480	3399480	3146045

Table A.14: Negative Binomial Regression Results: Machine Level, Minute Crowdedness: Standard errors are in parentheses and clustered at machine-level. Machine, day-of-week, and timing fixed effects are controlled.

	(1)	(2)	(3)
temperature	0.0786*** (0.00311)	0.0787*** (0.00311)	0.0781*** (0.00315)
precipitation	-0.00182*** (0.000369)	-0.00185*** (0.000370)	-0.00202*** (0.000374)
machine_PR	0.0646*** (0.00510)	0.0641*** (0.00523)	-0.000700 (0.00702)
crowdedness_minute_2	0.0167*** (0.00150)	0.0160*** (0.00149)	0.00714*** (0.00140)
departure	0.199*** (0.00953)		
machine_PR × crowdedness_minute_2	0.00154*** (0.000279)	0.00142*** (0.000277)	0.00100*** (0.000294)
machine_PR × departure	-0.0656*** (0.00688)		
departure_next1		0.264*** (0.00897)	
machine_PR × departure_next1		-0.0610*** (0.00735)	
time to next			-0.0829*** (0.00250)
time to after next			-0.0591*** (0.00283)
machine_PR × time to next			0.0130*** (0.00142)
machine_PR × time to after next			0.00299* (0.00140)
Constant	-3.836*** (0.0859)	-3.845*** (0.0857)	-2.932*** (0.0882)
lnalpha	-0.698*** (0.0444)	-0.712*** (0.0448)	-0.977*** (0.0503)
Observations	3399480	3399480	3146045

Table A.15: Negative Binomial Regression Results: Machine Level, Smoothed Minute Crowdedness: Standard errors are in parentheses and clustered at machine-level. Machine, day-of-week, and timing fixed effects are controlled.

(1)	
temperature	0.0796*** (0.00304)
precipitation	-0.00188*** (0.000353)
machine_PR	0.0377*** (0.00377)
product_PR	0.0362*** (0.00902)
Constant	-7.325*** (0.103)
<hr/>	
Inalpha	
Constant	1.121*** (0.0368)
Observations	108188100

Table A.16: Negative Binomial Regression Results: Product Level Base Model

We find our results quantitatively similar across subgroups, confirming that our main results are not driven solely by unobserved consumer heterogeneity as regards commuters or non-commuters.

Gender Information Moreover, among those who use commuter tickets, a significant fraction of consumers have signed up for the special loyalty program of the company, and their demographic information such as age, gender, and resident address is recorded. We use the demographic information to calculate the fraction of male consumers, and then split the sample into two subsamples with respect to the fraction of male customers. Some vending machines may attract more male than female consumers owing to location or assortment, and this difference may affect our main results, because male consumers may react differently to recommendations compared to female consumers. Also, male consumers and female consumers may experience time and crowd pressures differently. Tables A.23 and A.24 present the machine-level results, and Tables A.25 and A.26 present the product-level results. In each table, we split the sample into two subgroups based on the fraction of male customers. In order to save space, we do not report the results with *crowdedness_minute_1* as the proxy variable for crowd pressure, but the results are qualitatively similar to our main results.

	(1)	(2)	(3)
(sum) sales			
temperature	0.0796*** (0.00304)	0.0796*** (0.00304)	0.0801*** (0.00330)
precipitation	-0.00155*** (0.000351)	-0.00155*** (0.000351)	-0.00214*** (0.000410)
crowdedness_hour	0.000157*** (0.0000124)	0.000157*** (0.0000124)	0.0000879*** (0.0000116)
machine_PR	0.0493*** (0.00494)	0.0496*** (0.00492)	0.0225*** (0.00545)
product_PR	0.0804*** (0.0112)	0.0800*** (0.0112)	0.0548*** (0.0129)
departure	0.196*** (0.0120)		
machine_PR × crowdedness_hour	0.0000271*** (0.00000311)	0.0000273*** (0.00000311)	0.0000185*** (0.00000339)
product_PR × crowdedness_hour	-0.0000685*** (0.00000879)	-0.0000687*** (0.00000880)	-0.0000641*** (0.00000950)
machine_PR × departure	-0.0495*** (0.00661)		
product_PR × departure	-0.0357** (0.0133)		
departure_next1		0.199*** (0.0119)	
machine_PR × departure_next1		-0.0504*** (0.00656)	
product_PR × departure_next1		-0.0346** (0.0132)	
time to next			-0.000774*** (0.000193)
time to after next			0.000263 (0.000691)
machine_PR × time to next			0.000464** (0.000158)
machine_PR × time to after next			-0.000753 (0.000886)
product_PR × time to next			0.000714*** (0.000293)
product_PR × time to after next			-0.00308 (0.00165)
Constant	-7.439*** (0.105)	-7.439*** (0.105)	-7.189*** (0.114)
lnalpha			
Constant	1.097*** (0.0372)	1.097*** (0.0372)	0.935*** (0.0392)
Observations	108188100	108188100	81508361

Table A.17: Negative Binomial Regression Results: Product Level, Hour Crowdedness

	(1)	(2)	(3)
(sum) sales			
temperature	0.0800*** (0.00304)	0.0800*** (0.00305)	0.0804*** (0.00329)
precipitation	-0.00171*** (0.000352)	-0.00171*** (0.000352)	-0.00225*** (0.000411)
size_passenger_m	0.00766*** (0.000485)	0.00764*** (0.000485)	0.00503*** (0.000454)
machine_PR	0.0563*** (0.00493)	0.0567*** (0.00491)	0.0296*** (0.00528)
product_PR	0.0722*** (0.0109)	0.0718*** (0.0109)	0.0360** (0.0120)
departure	0.211*** (0.0130)		
machine_PR × size_passenger_m	0.000848*** (0.000172)	0.000855*** (0.000172)	0.000466*** (0.000202)
product_PR × size_passenger_m	-0.00281*** (0.000433)	-0.00282*** (0.000434)	-0.00283*** (0.000508)
machine_PR × departure	-0.0497*** (0.00655)		
product_PR × departure	-0.0489*** (0.0132)		
departure_next1		0.214*** (0.0129)	
machine_PR × departure_next1		-0.0506*** (0.00650)	
product_PR × departure_next1		-0.0479*** (0.0131)	
time to next			-0.000798*** (0.000197)
time to after next			0.000193 (0.000695)
machine_PR × time to next			0.000418*** (0.000159)
machine_PR × time to after next			-0.000786 (0.000886)
product_PR × time to next			0.000933** (0.000291)
product_PR × time to after next			-0.00293 (0.00165)
Constant	-7.418*** (0.104)	-7.418*** (0.104)	-7.178*** (0.113)
Inalpha			
Constant	1.103*** (0.0371)	1.103*** (0.0371)	0.936*** (0.0392)
Observations	108188100	108188100	81508361

Table A.18: Negative Binomial Regression Results: Product Level Smoothed Minute Crowdedness

Table A.19: Poisson Regression Results by Membership Fraction: Machine Level, Smoothed Minute Crowdedness

	Member Low			Member High		
	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.0783*** (0.00443)	0.0784*** (0.00443)	0.0779*** (0.00449)	0.0794*** (0.00444)	0.0794*** (0.00444)	0.0786*** (0.00446)
precipitation	-0.00344*** (0.000524)	-0.00346*** (0.000525)	-0.00358*** (0.000552)	-0.000629 (0.000504)	-0.000655 (0.000503)	-0.000875 (0.000498)
machine_PR	0.0680*** (0.00712)	0.0684*** (0.00757)	-0.00114 (0.00989)	0.0587*** (0.00717)	0.0572*** (0.00707)	0.000651 (0.00983)
crowdedness_minute_2	0.0129*** (0.00222)	0.0120*** (0.00221)	0.00377 (0.00203)	0.0189*** (0.00171)	0.0183*** (0.00169)	0.00932*** (0.00161)
departure	0.171*** (0.0128)			0.225*** (0.0143)		
machine_PR × crowdedness_minute_2	0.00156*** (0.000397)	0.00146*** (0.000388)	0.00105* (0.000420)	0.00152*** (0.000381)	0.00139*** (0.000381)	0.00101* (0.000408)
machine_PR × departure	-0.0667*** (0.00981)			-0.0596*** (0.00961)		
departure_next1		0.249*** (0.0126)			0.278*** (0.0129)	
machine_PR × departure_next1=1		-0.0639*** (0.0103)			-0.0537*** (0.0102)	
time to next			-0.0791*** (0.00390)			-0.0864*** (0.00295)
time to after next			-0.0588*** (0.00411)			-0.0609*** (0.00382)
machine_PR × time to next			0.0134*** (0.00201)			0.0124*** (0.00207)
machine_PR × time to after next			0.00387* (0.00192)			0.00170 (0.00196)
Constant	-3.803*** (0.120)	-3.813*** (0.119)	-2.932*** (0.123)	-3.413*** (0.137)	-3.429*** (0.136)	-2.658*** (0.136)
Observations	1651860	1651860	1520435	1747620	1747620	1625610

Table A.20: Poisson Regression Results by Member Fraction: Machine Level, Hour Crowdedness

	Member Low			Member High		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0783*** (0.00442)	0.0784*** (0.00442)	0.0780*** (0.00449)	0.0799*** (0.00443)	0.0799*** (0.00443)	0.0790*** (0.00445)
precipitation	-0.00344*** (0.000524)	-0.00346*** (0.000525)	-0.00355*** (0.000551)	-0.000615 (0.000505)	-0.000643 (0.000504)	-0.000860 (0.000501)
machine_PR	0.0691*** (0.00697)	0.0693*** (0.00746)	0.0000746 (0.00955)	0.0615*** (0.00716)	0.0599*** (0.00704)	0.00686 (0.00943)
crowdedness_hour	0.000158*** (0.0000287)	0.000149*** (0.0000284)	0.0000621*** (0.0000228)	0.000153*** (0.0000118)	0.000149*** (0.0000118)	0.0000888*** (0.0000115)
departure	0.175*** (0.0133)			0.236*** (0.0152)		
machine_PR × crowdedness_hour	0.0000233*** (0.00000531)	0.0000221*** (0.00000541)	0.0000177** (0.00000622)	0.0000129*** (0.00000374)	0.0000117** (0.00000388)	0.00000708* (0.00000309)
machine_PR × departure	-0.0661*** (0.00943)			-0.0577*** (0.00950)		
departure_next1		0.253*** (0.0131)			0.287*** (0.0138)	
machine_PR × departure_next1		-0.0633*** (0.0105)			-0.0518*** (0.0105)	
time to next			-0.0789*** (0.00387)			-0.0864*** (0.00296)
time to after next			-0.0584*** (0.00408)			-0.0607*** (0.00379)
machine_PR=1 × time to next			0.0132*** (0.00201)			0.0119*** (0.00209)
machine_PR=1 × time to after next			0.00367 (0.00190)			0.00110 (0.00193)
Constant	-3.786*** (0.120)	-3.797*** (0.119)	-2.936*** (0.123)	-3.114*** (0.123)	-3.141*** (0.122)	-2.528*** (0.122)
Observations	1651860	1651860	1520435	1747620	1747620	1625610

Table A.21: Poisson Regression Results by Membership Fraction: Product Level, Smoothed Minute Crowdedness

	Member Low			Member High		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0712*** (0.00396)	0.0713*** (0.00396)	0.0710*** (0.00427)	0.0909*** (0.00453)	0.0909*** (0.00453)	0.0921*** (0.00484)
precipitation	-0.00181*** (0.000462)	-0.00181*** (0.000462)	-0.00218*** (0.000525)	-0.00191*** (0.000526)	-0.00191*** (0.000526)	-0.00277*** (0.000617)
size_passenger_m	0.00874*** (0.00109)	0.00872*** (0.00109)	0.00530*** (0.000951)	0.00735*** (0.000532)	0.00735*** (0.000532)	0.00526*** (0.000513)
machine_PR	0.0632*** (0.00674)	0.0638*** (0.00677)	0.0328*** (0.00821)	0.0496*** (0.00704)	0.0497*** (0.00692)	0.0301*** (0.00696)
product_PR	0.0637*** (0.0140)	0.0631*** (0.0139)	0.0332 (0.0171)	0.0759*** (0.0171)	0.0758*** (0.0171)	0.0364* (0.0167)
departure	0.156*** (0.0142)			0.273*** (0.0221)		
machine_PR × size_passenger_m	0.00121*** (0.000340)	0.00122*** (0.000340)	0.000987*** (0.000427)	0.000574** (0.000198)	0.000575** (0.000198)	0.0000922 (0.000230)
product_PR × size_passenger_m	-0.00266*** (0.000890)	-0.00268*** (0.000891)	-0.00303** (0.00109)	-0.00245*** (0.000500)	-0.00246*** (0.000502)	-0.00223*** (0.000580)
machine_PR × departure	-0.0545*** (0.00929)			-0.0427*** (0.00923)		
product_PR × departure	-0.0473** (0.0183)			-0.0467** (0.0190)		
departure_next1		0.160*** (0.0140)			0.275*** (0.0219)	
machine_PR × departure_next1		-0.0562*** (0.00918)			-0.0428*** (0.00920)	
product_PR × departure_next1		-0.0456** (0.0176)			-0.0464** (0.0194)	
time to next			-0.000343 (0.000248)			-0.00130*** (0.000320)
time to after next			0.000144 (0.000885)			0.000307 (0.00110)
machine_PR × time to next			0.000571** (0.000212)			0.000503** (0.000239)
machine_PR × time to after next			-0.00145 (0.00115)			-0.0000264 (0.00137)
product_PR × time to next			0.000888** (0.000388)			0.000826** (0.000334)
product_PR × time to after next			-0.00199 (0.00206)			-0.00417 (0.00267)
Constant	-7.538*** (0.115)	-7.539*** (0.116)	-7.175*** (0.129)	-7.789*** (0.144)	-7.790*** (0.144)	-7.566*** (0.155)
Observations	54777840	54777840	40625830	53410260	53410260	40882531

Table A.22: Poisson Regression Results by Membership Fraction: Product Level, Hour Crowdedness

	Member Low			Member High		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0711*** (0.00396)	0.0711*** (0.00396)	0.0709*** (0.00428)	0.0901*** (0.00455)	0.0901*** (0.00455)	0.0916*** (0.00488)
precipitation	-0.00171*** (0.000462)	-0.00171*** (0.000462)	-0.00214*** (0.000525)	-0.00166** (0.000518)	-0.00166** (0.000518)	-0.00259*** (0.000615)
crowdedness_hour	0.000184*** (0.0000246)	0.000183*** (0.0000246)	0.0000922*** (0.0000197)	0.000159*** (0.0000150)	0.000159*** (0.0000150)	0.0000998*** (0.0000146)
machine_PR	0.0592*** (0.00675)	0.0599*** (0.00677)	0.0308*** (0.00806)	0.0386*** (0.00694)	0.0386*** (0.00683)	0.0200** (0.00759)
product_PR	0.0682*** (0.0143)	0.0676*** (0.0141)	0.0421* (0.0177)	0.0895*** (0.0177)	0.0894*** (0.0178)	0.0630*** (0.0188)
departure	0.146*** (0.0140)			0.248*** (0.0192)		
machine_PR × crowdedness_hour	0.0000274*** (0.00000537)	0.0000277*** (0.00000535)	0.0000195** (0.00000599)	0.0000247*** (0.00000399)	0.0000247*** (0.00000400)	0.0000145*** (0.00000436)
product_PR × crowdedness_hour	-0.0000626*** (0.0000180)	-0.0000630*** (0.0000180)	-0.0000621* (0.0000200)	-0.0000661*** (0.0000103)	-0.0000661*** (0.0000103)	-0.0000572*** (0.0000110)
machine_PR × departure	-0.0517*** (0.00928)			-0.0426*** (0.00938)		
product_PR × departure	-0.0419* (0.0183)			-0.0481* (0.0192)		
departure_next1		0.150*** (0.0138)			0.249*** (0.0191)	
machine_PR × departure_next1		-0.0534*** (0.00915)			-0.0427*** (0.00938)	
product_PR × departure_next1		-0.0401* (0.0176)			-0.0478* (0.0196)	
time to next			-0.000336 (0.000247)			-0.00118*** (0.000299)
time to after next			0.000189 (0.000885)			0.000460 (0.00109)
machine_PR × time to next			0.000570** (0.000208)			0.000150 (0.000241)
machine_PR × time to after next			-0.00145 (0.00115)			0.00000987 (0.00137)
product_PR × time to next			0.000794* (0.000391)			0.000535* (0.000238)
product_PR × time to after next			-0.00205 (0.00206)			-0.00438 (0.00267)
Constant	-7.547*** (0.116)	-7.548*** (0.116)	-7.178*** (0.129)	-7.815*** (0.146)	-7.815*** (0.146)	-7.587*** (0.157)
Observations	54777840	54777840	40625830	53410260	53410260	40882531

Table A.23: Poisson Regression Results by Gender Fraction: Machine Level, Smoothed Minute Crowdedness

	Male Low			Male High		
	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.0696*** (0.00403)	0.0696*** (0.00403)	0.0685*** (0.00402)	0.0904*** (0.00472)	0.0905*** (0.00472)	0.0904*** (0.00477)
precipitation	-0.00191*** (0.000485)	-0.00193*** (0.000485)	-0.00204*** (0.000480)	-0.00217*** (0.000545)	-0.00220*** (0.000546)	-0.00242*** (0.000574)
machine_PR	0.0745*** (0.00682)	0.0754*** (0.00682)	0.00617 (0.0101)	0.0538*** (0.00752)	0.0513*** (0.00801)	-0.00314 (0.00981)
crowdedness_minute_2	0.0176*** (0.00200)	0.0166*** (0.00197)	0.00734*** (0.00189)	0.0171*** (0.00204)	0.0166*** (0.00205)	0.00794*** (0.00196)
departure	0.167*** (0.0126)			0.225*** (0.0138)		
machine_PR × crowdedness_minute_2	0.00159*** (0.000435)	0.00149*** (0.000429)	0.000891 (0.000469)	0.00138*** (0.000366)	0.00124*** (0.000364)	0.00103** (0.000385)
machine_PR × departure	-0.0703*** (0.00915)			-0.0569*** (0.0104)		
departure_next1		0.255*** (0.0114)			0.264*** (0.0137)	
machine_PR × departure_next1		-0.0684*** (0.00935)			-0.0492*** (0.0115)	
time to next			-0.0837*** (0.00338)			-0.0802*** (0.00364)
time to after next			-0.0578*** (0.00379)			-0.0614*** (0.00409)
machine_PR × time to next			0.0138*** (0.00192)			0.0114*** (0.00208)
machine_PR × time to after next			0.00334 (0.00196)			0.00173 (0.00200)
Constant	-3.799*** (0.111)	-3.812*** (0.111)	-2.832*** (0.112)	-4.247*** (0.127)	-4.251*** (0.127)	-3.333*** (0.132)
Observations	1739640	1739640	1609585	1659840	1659840	1536460

Table A.24: Poisson Regression Results by Gender Fraction: Machine Level, Hourly Crowdedness

	Male Low			Male High		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0697*** (0.00403)	0.0697*** (0.00403)	0.0685*** (0.00402)	0.0907*** (0.00468)	0.0908*** (0.00468)	0.0908*** (0.00474)
precipitation	-0.00192*** (0.000486)	-0.00194*** (0.000486)	-0.00203*** (0.000482)	-0.00215*** (0.000546)	-0.00218*** (0.000548)	-0.00240*** (0.000576)
machine_PR	0.0755*** (0.00673)	0.0763*** (0.00677)	0.00840 (0.0100)	0.0562*** (0.00740)	0.0535*** (0.00787)	0.00503 (0.00931)
crowdedness_hour	0.000196*** (0.0000272)	0.000186*** (0.0000265)	0.0000943*** (0.0000202)	0.000159*** (0.0000135)	0.000156*** (0.0000136)	0.0000942*** (0.0000136)
departure	0.169*** (0.0135)			0.234*** (0.0144)		
machine_PR × crowdedness_hour	0.0000176** (0.00000572)	0.0000166** (0.00000582)	0.0000101 (0.00000573)	0.0000130*** (0.00000394)	0.0000116** (0.00000409)	0.00000774 (0.00000435)
machine_PR × departure	-0.0684*** (0.00909)			-0.0538*** (0.0102)		
departure_next1		0.256*** (0.0125)			0.273*** (0.0142)	
machine_PR × departure_next1		-0.0665*** (0.00978)			-0.0462*** (0.0117)	
time to next			-0.0835*** (0.00338)			-0.0798*** (0.00359)
time to after next			-0.0575*** (0.00378)			-0.0608*** (0.00403)
machine_PR × time to next			0.0136*** (0.00193)			0.0107*** (0.00208)
machine_PR × time to after next			0.00308 (0.00195)			0.000850 (0.00197)
Constant	-3.803*** (0.111)	-3.815*** (0.111)	-2.841*** (0.111)	-4.223*** (0.125)	-4.227*** (0.125)	-3.341*** (0.128)
Observations	1739640	1739640	1609585	1659840	1659840	1536460

Table A.25: Poisson Regression Results by Gender Fraction: Product-Level, Smoothed Minute Crowdedness

	Male Low			Male High		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0712*** (0.00396)	0.0713*** (0.00396)	0.0710*** (0.00427)	0.0909*** (0.00453)	0.0909*** (0.00453)	0.0921*** (0.00484)
precipitation	-0.00181*** (0.000462)	-0.00181*** (0.000462)	-0.00218*** (0.000525)	-0.00191*** (0.000526)	-0.00191*** (0.000526)	-0.00277*** (0.000617)
size_passenger_minute	0.00874*** (0.00109)	0.00872*** (0.00109)	0.00530*** (0.000951)	0.00735*** (0.000532)	0.00735*** (0.000532)	0.00526*** (0.000513)
machine_PR	0.0632*** (0.00674)	0.0638*** (0.00677)	0.0328*** (0.00821)	0.0496*** (0.00704)	0.0497*** (0.00692)	0.0301*** (0.00696)
product_PR	0.0637*** (0.0140)	0.0631*** (0.0139)	0.0332* (0.0151)	0.0759*** (0.0171)	0.0758*** (0.0171)	0.0364*** (0.0167)
departure	0.156*** (0.0142)			0.273*** (0.0221)		
machine_PR × size_passenger_minute	0.00121*** (0.000340)	0.00122*** (0.000340)	0.000987** (0.000427)	0.000574** (0.000198)	0.000575** (0.000198)	0.0000922 (0.000230)
product_PR × size_passenger_minute	-0.00266** (0.000890)	-0.00268** (0.000891)	-0.00303** (0.00109)	-0.00245*** (0.000500)	-0.00246*** (0.000502)	-0.00223*** (0.000580)
machine_PR × departure	-0.0545*** (0.00929)			-0.0427*** (0.00923)		
product_PR × departure	-0.0473** (0.0183)			-0.0467* (0.0190)		
departure_next1		0.160*** (0.0140)			0.275*** (0.0219)	
machine_PR × departure_next1		-0.0562*** (0.00918)			-0.0428*** (0.00920)	
product_PR × departure_next1		-0.0456** (0.0176)			-0.0464* (0.0194)	
time to next			-0.000343 (0.000248)			-0.00130*** (0.000320)
time to after next			0.000144 (0.000885)			0.000307 (0.00110)
machine_PR × time to next			0.000571** (0.000212)			0.000103 (0.000239)
machine_PR × time to after next			-0.00145 (0.00115)			-0.0000264 (0.00137)
product_PR × time to next			0.000888* (0.000388)			0.000826* (0.000404)
product_PR × time to after next			-0.00199 (0.00206)			-0.00417 (0.00267)
Constant	-7.538*** (0.115)	-7.539*** (0.116)	-7.175*** (0.129)	-7.789*** (0.144)	-7.790*** (0.144)	-7.566*** (0.155)
Observations	54777840	54777840	40625830	53410260	53410260	40882531

Table A.26: Poisson Regression Results by Gender Fraction: Product Level, Hour Crowdedness

	Male Low (1)	(2)	(3)	Male High (4)	(5)	(6)
(sum) sales						
temperature	0.0794*** (0.00440)	0.0794*** (0.00440)	0.0812*** (0.00472)	0.0799*** (0.00421)	0.0799*** (0.00421)	0.0796*** (0.00459)
precipitation	-0.00296*** (0.000498)	-0.00296*** (0.000498)	-0.00383*** (0.000589)	-0.000432 (0.000482)	-0.000434 (0.000482)	-0.000832 (0.000544)
crowdedness_hour	0.000141*** (0.0000300)	0.000141*** (0.0000300)	0.0000550*** (0.0000252)	0.000155*** (0.0000120)	0.000155*** (0.0000120)	0.0000946*** (0.0000117)
machine_PR	0.0516*** (0.00680)	0.0525*** (0.00676)	0.0232** (0.00766)	0.0447*** (0.00715)	0.0444*** (0.00715)	0.0226** (0.00763)
product_PR	0.0721*** (0.0151)	0.0711*** (0.0149)	0.0613*** (0.0181)	0.0874*** (0.0168)	0.0877*** (0.0168)	0.0453* (0.0186)
departure	0.161*** (0.0142)			0.236*** (0.0194)		
machine_PR × crowdedness_hour	0.0000319*** (0.00000591)	0.0000324*** (0.00000589)	0.0000237*** (0.00000655)	0.0000249*** (0.00000372)	0.0000248*** (0.00000371)	0.0000164*** (0.00000403)
product_PR × crowdedness_hour	-0.0000546** (0.0000170)	-0.0000551** (0.0000171)	-0.0000530** (0.0000193)	-0.0000708*** (0.0000101)	-0.0000707*** (0.0000101)	-0.0000632*** (0.0000107)
machine_PR × departure	-0.0506*** (0.00903)			-0.0449*** (0.00954)		
product_PR × departure	-0.0445* (0.0184)			-0.0462* (0.0190)		
departure_next1		0.164*** (0.0141)			0.239*** (0.0192)	
machine_PR × departure_next1		-0.0532*** (0.00894)			-0.0441*** (0.00952)	
product_PR × departure_next1		-0.0216 (0.0178)			-0.0470* (0.0192)	
time to next			-0.000533* (0.000259)			-0.00110*** (0.000290)
time to after next			0.000318 (0.000855)			0.000177 (0.00112)
machine_PR × time to next			0.000532** (0.000202)			0.000510* (0.000244)
machine_PR × time to after next			-0.000606 (0.00105)			-0.000981 (0.00148)
product_PR × time to next			0.000815* (0.000396)			0.000907* (0.000427)
product_PR × time to after next			-0.00519* (0.00228)			-0.000796 (0.00235)
Constant	-7.397*** (0.137)	-7.398*** (0.137)	-7.211*** (0.145)	-6.546*** (0.151)	-6.548*** (0.152)	-6.213*** (0.162)
Observations	52337820	52337820	38912074	55850280	55850280	42596287

Again, the main results hold for both groups. The results show that our estimates are consistent across both groups and thus the main results are not driven by consumer heterogeneity due to gender.

A.4.3 Robustness Check 3: Location of Vending Machines

Another robustness check discussed in Section 4.5 is regarding the location where the vending machines are placed. In particular, we consider the vending machines placed on platforms and those placed on the concourse. Consumers may experience different time and crowd pressure levels when making purchases at platform and concourse. Also, consumers may self-select into different vending machines depending on the time pressure and crowd pressure they experience. Tables A.27 (*crowdedness_minute_2* as the proxy for crowd pressure) and A.28 (*crowdedness_hour* as the proxy for crowd pressure) present the machine-level results for the subsamples of vending machines placed on the platform and on the concourse, respectively. Tables A.29 (*crowdedness_minute_2* as the proxy for crowd pressure) and A.30 (*crowdedness_hour* as the proxy for crowd pressure) present the product-level results for the two subsamples. In order to save space, we do not report the results with *crowdedness_minute_1* as the proxy variable for crowd pressure, but the results are qualitatively similar to our main results.

We find the results quite consistent across subgroups. Although some coefficients are statistically significant for only the platform subsample due to its larger sample size, the signs are always consistent. Therefore, we confirm that our main results hold even when we split the sample based on the location where the vending machines are placed.

A.4.4 Robustness Check 4: Hourly Fixed Effects

One of the robustness checks discussed in Section 5 relates to the inclusion of hour fixed effect instead of time-of-day fixed effect. We report the machine-level results in Tables A.31, A.32, and A.33, and the product-level results in Tables A.34 and A.35. As the measure of crowd pres-

Table A.27: Poisson Regression Results: Machine Level, Smoothed Minute Crowdedness, Platform and Concourse

	Platform			Concourse		
	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.0780*** (0.00358)	0.0781*** (0.00358)	0.0772*** (0.00359)	0.0805*** (0.00713)	0.0806*** (0.00714)	0.0795*** (0.00727)
precipitation	-0.00209*** (0.000506)	-0.00213*** (0.000506)	-0.00236*** (0.000504)	-0.00146** (0.000552)	-0.00147** (0.000551)	-0.00157** (0.000561)
machine_PR	0.0665*** (0.00560)	0.0675*** (0.00586)	-0.00915 (0.00821)	0.0527*** (0.0112)	0.0478*** (0.0108)	0.00922 (0.0145)
crowdedness_minute_2	0.0153*** (0.00205)	0.0141*** (0.00203)	0.00445* (0.00189)	0.0168*** (0.00211)	0.0171*** (0.00212)	0.0102*** (0.00207)
departure	0.179*** (0.0119)			0.251*** (0.0148)		
machine_PR × crowdedness_minute_2	0.00125*** (0.000329)	0.00113*** (0.000329)	0.000713* (0.000359)	0.00259*** (0.000442)	0.00242*** (0.000447)	0.00204*** (0.000476)
machine_PR × departure	-0.0692*** (0.00758)			-0.0567*** (0.0143)		
departure_next1		0.277*** (0.0109)			0.224*** (0.0157)	
machine_PR × departure_next1		-0.0672*** (0.00817)			-0.0442** (0.0151)	
time to next			-0.0896*** (0.00318)			-0.0666*** (0.00347)
time to after next			-0.0602*** (0.00355)			-0.0560*** (0.00466)
machine_PR × time to next			0.0158*** (0.00159)			0.00799** (0.00258)
machine_PR × time to after next			0.00398* (0.00165)			0.000631 (0.00277)
Constant	-3.847*** (0.0990)	-3.859*** (0.0988)	-2.906*** (0.101)	-3.304*** (0.213)	-3.298*** (0.213)	-2.659*** (0.216)
Observations	2290260	2290260	2127809	1005480	1005480	928265

Table A.28: Poisson Regression Results: Machine-Level, Hour Crowdedness, Platform and Concourse

	Platform			Concourse		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0780*** (0.00356)	0.0781*** (0.00356)	0.0773*** (0.00358)	0.0814*** (0.00713)	0.0815*** (0.00714)	0.0802*** (0.00726)
precipitation	-0.00208*** (0.000506)	-0.00212*** (0.000506)	-0.00232*** (0.000504)	-0.00143** (0.000554)	-0.00144** (0.000553)	-0.00155** (0.000563)
machine_PR	0.0673*** (0.00556)	0.0682*** (0.00582)	0.00668 (0.00788)	0.0569*** (0.0110)	0.0519*** (0.0106)	0.0217 (0.0142)
crowdedness_hour	0.000156*** (0.0000169)	0.000146*** (0.0000167)	0.0000689*** (0.0000147)	0.000155*** (0.0000151)	0.000158*** (0.0000152)	0.000107*** (0.0000153)
departure	0.184*** (0.0124)			0.256*** (0.0162)		
machine_PR × crowdedness_hour	0.0000147*** (0.00000359)	0.0000135*** (0.00000380)	0.00000896* (0.00000423)	0.0000221*** (0.00000564)	0.0000204*** (0.00000583)	0.0000158** (0.00000609)
machine_PR × departure	-0.0680*** (0.00731)			-0.0492*** (0.0144)		
departure_next1		0.282*** (0.0112)			0.229*** (0.0174)	
machine_PR × departure_next1		-0.0660*** (0.00826)			-0.0369** (0.0157)	
time to next			-0.0891*** (0.00314)			-0.0665*** (0.00346)
time to after next			-0.0596*** (0.00350)			-0.0556*** (0.00459)
machine_PR × time to next			0.0155*** (0.00159)			0.00725** (0.00261)
machine_PR × time to after next			0.00360* (0.00163)			-0.000559 (0.00274)
Constant	-3.823*** (0.0981)	-3.838*** (0.0979)	-2.914*** (0.100)	-3.067*** (0.196)	-3.058*** (0.196)	-2.533*** (0.199)
Observations	2290260	2290260	2127809	1005480	1005480	928265

Table A.29: Poisson Regression Results: Product-Level, Smoothed Minute Crowdedness, Platform and Concourse

	Platform			Concourse		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales temperature	0.0786*** (0.00347)	0.0787*** (0.00347)	0.0794*** (0.00366)	0.0843*** (0.00636)	0.0843*** (0.00637)	0.0845*** (0.00721)
precipitation	-0.00200*** (0.000479)	-0.00200*** (0.000479)	-0.00264*** (0.000549)	-0.00135*** (0.000515)	-0.00135*** (0.000515)	-0.00169*** (0.000593)
size_passenger_m	0.00709*** (0.000642)	0.00707*** (0.000642)	0.00414*** (0.000575)	0.00759*** (0.000608)	0.00760*** (0.000609)	0.00579*** (0.000595)
machine_PR	0.0576*** (0.00557)	0.0586*** (0.00555)	0.0261*** (0.00620)	0.0559*** (0.0103)	0.0547*** (0.0103)	0.0376*** (0.0103)
product_PR	0.0564*** (0.0123)	0.0561*** (0.0121)	0.0364*** (0.0143)	0.0986*** (0.0221)	0.0981*** (0.0228)	0.0307** (0.0113)
departure	0.173*** (0.0155)			0.314*** (0.0223)		
machine_PR × size_passenger_m	0.000764*** (0.000221)	0.000783*** (0.000221)	0.000390 (0.000269)	0.000955*** (0.000265)	0.000935*** (0.000264)	0.000584* (0.000297)
product_PR × size_passenger_m	-0.00248*** (0.000476)	-0.00249*** (0.000479)	-0.00258*** (0.000591)	-0.00271*** (0.000726)	-0.00272*** (0.000725)	-0.00256*** (0.000804)
machine_PR × departure	-0.0557*** (0.00733)			-0.0394*** (0.0137)		
product_PR × departure	-0.0280* (0.0133)			-0.0878*** (0.0230)		
departure_next1		0.178*** (0.0153)			0.313*** (0.0226)	
machine_PR × departure_next1		-0.0580*** (0.00733)			-0.0364*** (0.0134)	
product_PR × departure_next1		-0.0371* (0.0149)			-0.0866*** (0.0240)	
time to next			-0.000490** (0.000227)			-0.00182*** (0.000391)
time to after next			0.000141 (0.000806)			0.000288 (0.00137)
machine_PR × time to next			0.000559** (0.000184)			0.000103 (0.000314)
machine_PR × time to after next			-0.00115 (0.00106)			0.000355 (0.00160)
product_PR × time to next			0.000732* (0.000331)			0.00120* (0.000560)
product_PR × time to after next			-0.00285 (0.00189)			-0.00333 (0.00343)
Constant	-7.408*** (0.109)	-7.409*** (0.109)	-7.182*** (0.113)	-6.479*** (0.250)	-6.478*** (0.250)	-6.187*** (0.268)
Observations	71210280	71210280	54835915	36977820	36977820	26672446

Table A.30: Poisson Regression Results: Product-Level, Hour Crowdedness, Platform and Concourse

	Platform			Concourse		
	(1)	(2)	(3)	(4)	(5)	(6)
(sum) sales						
temperature	0.0783*** (0.00347)	0.0783*** (0.00347)	0.0792*** (0.00367)	0.0837*** (0.00636)	0.0837*** (0.00637)	0.0840*** (0.00723)
precipitation	-0.00185*** (0.000480)	-0.00185*** (0.000480)	-0.00256*** (0.000550)	-0.00115* (0.000507)	-0.00116* (0.000506)	-0.00152* (0.000583)
crowdedness_hour	0.000144*** (0.0000176)	0.000143*** (0.0000176)	0.0000652*** (0.0000159)	0.000129*** (0.0000134)	0.000161*** (0.0000138)	0.000111*** (0.0000137)
machine_PR	0.0522*** (0.00554)	0.0532*** (0.00553)	0.0211*** (0.00632)	0.0443*** (0.0104)	0.0434*** (0.0103)	0.0253* (0.0110)
product_PR	0.0620*** (0.0125)	0.0616*** (0.0123)	0.0476** (0.0150)	0.115*** (0.0232)	0.115*** (0.0238)	0.0673** (0.0250)
departure	0.162*** (0.0144)			0.289*** (0.0195)		
machine_PR × crowdedness_hour	0.0000238*** (0.00000395)	0.0000242*** (0.00000395)	0.0000147*** (0.00000437)	0.0000317*** (0.00000504)	0.0000311*** (0.00000497)	0.0000237*** (0.00000535)
product_PR × crowdedness_hour	-0.0000564*** (0.0000104)	-0.0000565*** (0.0000104)	-0.0000520*** (0.0000114)	-0.0000883*** (0.0000199)	-0.0000787*** (0.0000146)	-0.0000718*** (0.0000153)
machine_PR × departure	-0.0552*** (0.00733)			-0.0395** (0.0139)		
product_PR × departure	-0.0201 (0.0156)			-0.0637** (0.0229)		
departure_next1		0.167*** (0.0142)			0.290*** (0.0195)	
machine_PR × departure_next1		-0.0576*** (0.00735)			-0.0370** (0.0135)	
product_PR × departure_next1		-0.0191 (0.0152)			-0.0619** (0.0237)	
time to next			-0.000498* (0.000223)			-0.00172*** (0.000368)
time to after next			0.000172 (0.000803)			0.000451 (0.00136)
machine_PR × time to next			0.000602*** (0.000183)			0.000159 (0.000112)
machine_PR × time to after next			-0.00112 (0.00106)			0.000396 (0.00160)
product_PR × time to next			0.000702* (0.000337)			0.000792* (0.000359)
product_PR × time to after next			-0.00294 (0.00189)			-0.00360 (0.00342)
Constant	-7.425*** (0.109)	-7.426*** (0.109)	-7.186*** (0.114)	-6.578*** (0.253)	-6.581*** (0.253)	-6.263*** (0.272)
Observations	71210280	71210280	54835915	36977820	36977820	26672446

sure, we use *crowd_hour* in Table A.31, *crowd_minute1* in Table A.32 and *crowd_minute2* in Table A.33. Similarly, we use *crowd_hour* in Table A.34 and *crowd_minute2* in Table A.35. In each table, as in the main text, there are three variables to measure time pressure, *departure*, *departure_next1*, and *time_to_next*.

Table A.31: Poisson Regression Results: Machine Level, Hour Crowdedness, Hour Fixed Effect

	(1)	(2)	(3)
temperature	0.0791*** (0.00318)	0.0791*** (0.00317)	0.0789*** (0.00321)
precipitation	-0.00228*** (0.000373)	-0.00228*** (0.000373)	-0.00232*** (0.000380)
machine_PR	0.0471*** (0.00498)	0.0458*** (0.00508)	0.0267*** (0.00661)
crowdedness_hour	-0.0000679*** (0.0000137)	-0.0000677*** (0.0000138)	-0.0000507*** (0.0000133)
departure	-0.0568*** (0.00719)		
machine_PR × crowdedness_hour	0.00000774* (0.00000355)	0.00000695 (0.00000364)	0.00000821* (0.00000364)
machine_PR × departure	-0.0151* (0.00663)		
departure_next1		0.0120 (0.00673)	
machine_PR × departure_next1		-0.0111 (0.00730)	
time to next			-0.0368*** (0.00207)
time to after next			-0.0178*** (0.00241)
machine_PR × time to next			0.00664*** (0.00143)
machine_PR × time to after next			-0.000748 (0.00132)
Constant	-5.844*** (0.104)	-5.826*** (0.104)	-5.063*** (0.115)
Observations	3399480	3399480	3146045

Standard errors are in parentheses and are clustered at the machine level.

We find the results quantitatively quite similar to the results in the main text. Although some coefficients are statistically insignificant, their sign never change. Since the hour fixed

Table A.32: Poisson Regression Results: Machine Level, Minute Crowdedness, Hour Fixed Effect

	(1)	(2)	(3)
temperature	0.0793*** (0.00317)	0.0793*** (0.00317)	0.0792*** (0.00320)
precipitation	-0.00221*** (0.000374)	-0.00221*** (0.000374)	-0.00227*** (0.000381)
machine_PR	0.0463*** (0.00495)	0.0448*** (0.00506)	0.0336*** (0.00636)
crowdedness_minute_1	-0.00148** (0.000504)	-0.00152** (0.000510)	-0.000922 (0.000480)
departure	-0.0612*** (0.00721)		
machine_PR × crowdedness_minute_1	0.000186 (0.000247)	0.000134 (0.000249)	0.000185 (0.000245)
machine_PR × departure	-0.00717 (0.00673)		
departure_next1		0.00708 (0.00669)	
machine_PR × departure_next1		-0.00330 (0.00718)	
time to next			-0.0374*** (0.00209)
time to after next			-0.0188*** (0.00240)
machine_PR × time to next			0.00602*** (0.00142)
machine_PR × time to after next			-0.00157 (0.00131)
Constant	-5.838*** (0.104)	-5.820*** (0.104)	-5.033*** (0.115)
Observations	3399480	3399480	3146045

Table A.33: Poisson Regression Results: Machine Level, Smoothed Minute Crowdedness, Hour Fixed Effect

	(1)	(2)	(3)
temperature	0.0792*** (0.00317)	0.0792*** (0.00317)	0.0790*** (0.00321)
precipitation	-0.00231*** (0.000373)	-0.00232*** (0.000373)	-0.00235*** (0.000380)
machine_PR	0.0474*** (0.00507)	0.0462*** (0.00519)	0.0269*** (0.00682)
crowdedness_minute_2	-0.00713*** (0.00148)	-0.00720*** (0.00149)	-0.00570*** (0.00145)
departure	-0.0556*** (0.00724)		
machine_PR × crowdedness_minute_2	0.000454 (0.000288)	0.000377 (0.000288)	0.000519 (0.000289)
machine_PR × departure	-0.0145* (0.00671)		
departure_next1		0.0132* (0.00670)	
machine_PR × departure_next1		-0.0105 (0.00718)	
time to next			-0.0369*** (0.00208)
time to after next			-0.0180*** (0.00241)
machine_PR × time to next			0.00666*** (0.00143)
machine_PR × time to after next			-0.000684 (0.00133)
Constant	-5.846*** (0.104)	-5.829*** (0.104)	-5.065*** (0.115)
Observations	3399480	3399480	3146045

Table A.34: Poisson Regression Results Robustness: Product Level, Hour Crowdedness, Hour Fixed Effect

	(1)	(2)	(3)
temperature	0.0798*** (0.00308)	0.0798*** (0.00308)	0.0798*** (0.00334)
precipitation	-0.00195*** (0.000356)	-0.00195*** (0.000356)	-0.00250*** (0.000411)
crowdedness_hour	-0.0000726*** (0.0000151)	-0.0000727*** (0.0000151)	-0.0000707*** (0.0000149)
machine_PR	0.0318*** (0.00497)	0.0321*** (0.00498)	0.0282*** (0.00564)
product_PR	0.0896*** (0.0113)	0.0890*** (0.0112)	0.0572** (0.0129)
departure	-0.0585*** (0.00715)		
machine_PR × crowdedness_hour	0.0000186*** (0.00000369)	0.0000187*** (0.00000371)	0.0000175*** (0.00000374)
product_PR × crowdedness_hour	-0.0000748*** (0.0000103)	-0.0000751*** (0.0000103)	-0.0000738*** (0.0000103)
machine_PR × departure	-0.00579 (0.00655)		
product_PR × departure	-0.0378** (0.0134)		
departure_next1		-0.0561*** (0.00714)	
machine_PR × departure_next1		-0.00666 (0.00653)	
product_PR × departure_next1		-0.0363** (0.0135)	
time to next			0.00141*** (0.000152)
time to after next			0.000199 (0.000629)
machine_PR × time to next			0.00000564 (0.000155)
machine_PR × time to after next			-0.000254 (0.000912)
product_PR × time to next			0.000976*** (0.000279)
product_PR × time to after next			0.0000551 (0.00173)
Constant	-8.351*** (0.114)	-8.351*** (0.114)	-8.185*** (0.130)
Observations	108188100	108188100	81508353

Table A.35: Poisson Regression Results Robustness: Product Level, Smoothed Minute Crowdedness, Hour Fixed Effect

	(1)	(2)	(3)
temperature	0.0798*** (0.00308)	0.0798*** (0.00308)	0.0798*** (0.00333)
precipitation	-0.00199*** (0.000357)	-0.00199*** (0.000357)	-0.00254*** (0.000411)
crowdedness_minute2	-0.00775*** (0.00164)	-0.00776*** (0.00164)	-0.00765*** (0.00163)
machine_PR	0.0320*** (0.00509)	0.0323*** (0.00510)	0.0283*** (0.00590)
product_PR	0.0900*** (0.0116)	0.0894*** (0.0116)	0.0560*** (0.0143)
departure	-0.0568*** (0.00721)		
machine_PR × crowdedness_minute2	0.00120*** (0.000341)	0.00122*** (0.000342)	0.00117*** (0.000337)
product_PR × crowdedness_minute2	-0.00496*** (0.00103)	-0.00498*** (0.00102)	-0.00487*** (0.00102)
machine_PR × departure	-0.00523 (0.00662)		
product_PR × departure	-0.0397** (0.0140)		
departure_next1		-0.0543*** (0.00720)	
machine_PR × departure_next1		-0.00612 (0.00659)	
product_PR × departure_next1		-0.0381** (0.0140)	
time to next			0.00139*** (0.000153)
time to after next			0.000177 (0.000628)
machine_PR × time to next			0.00000924 (0.000154)
machine_PR × time to after next			-0.000272 (0.000911)
product_PR × time to next			0.000996*** (0.000287)
product_PR × time to after next			0.000104 (0.00173)
Constant	-8.357*** (0.113)	-8.357*** (0.113)	-8.193*** (0.129)
Observations	108188100	108188100	81508353

effect can capture time-varying unobserved heterogeneity, such as the time-varying mix of consumers, this robustness check confirms that our main results cannot be explained solely by the unobserved heterogeneity that varies by hour and machine.

A.5 Zero Inflated Poisson Regression

In the main text, we estimate Poisson regression models. A concern one might wonder is that customers do not buy beverages very frequently and hence there are too many zeros in the data. To see whether our results are driven by this fact, we estimate Zero Inflated Poisson (ZIP) models and report the results of the machine-level models.

Tables A.36 and A.37 report the results of ZIP models. We find that the results are similar to the ones in the main text. Hence, our results are robust to the existence of excessive amount of zeros in sales.

B Details on the Validity Check

B.1 Instruction for the first manipulation check experiment

The purpose of this experiment is to investigate what kind of factors affects performance when a subject conducts various tasks using public transportation within limited time.

I would like you to conduct the specified tasks at the specified stations. After leaving this room, take JR train from Kunitachi station and follow the route specified below. Fill in the survey immediately after the tasks are completely in each station.

- Kunitachi Station
 - Buy a ticket to Tachikawa station.
- Tachikawa Station
 - Task 1: Record the words written under the big display at Isetan store at North exit.

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.0790*** (0.00309)	0.0791*** (0.00310)	0.0784*** (0.00314)	0.0787*** (0.00310)	0.0787*** (0.00310)	0.0781*** (0.00314)
precipitation	-0.00199*** (0.000371)	-0.00200*** (0.000371)	-0.00210*** (0.000376)	-0.00183*** (0.000369)	-0.00185*** (0.000369)	-0.00202*** (0.000373)
machine_PR	0.0721*** (0.00507)	0.0712*** (0.00521)	0.00808 (0.00641)	0.0644*** (0.00512)	0.0641*** (0.00525)	-0.000794 (0.00700)
crowdedness_minute_1	0.00787*** (0.000518)	0.00774*** (0.000516)	0.00500*** (0.000454)			
departure	0.217*** (0.0104)			0.197*** (0.00948)		
machine_PR × crowdedness_minute_1	0.000383* (0.000166)	0.000330* (0.000166)	0.0000955 (0.000200)			
machine_PR × departure	-0.0657*** (0.00678)			-0.0654*** (0.00689)		
departure_next1		0.283*** (0.00947)			0.263*** (0.00891)	
machine_PR × departure_next1		-0.0616*** (0.00729)			-0.0614*** (0.00733)	
time to next			-0.0833*** (0.00249)			-0.0828*** (0.00250)
time to after next			-0.0591*** (0.00282)			-0.0589*** (0.00282)
machine_PR × time to next			0.0125*** (0.00142)			0.0130*** (0.00142)
machine_PR × time to after next			0.00238 (0.00137)			0.00300* (0.00140)
crowdedness_minute_2				0.0164*** (0.00147)	0.0157*** (0.00146)	0.00700*** (0.00139)
machine_PR=1 × crowdedness_minute_2				0.00154*** (0.000276)	0.00142*** (0.000275)	0.000996*** (0.000292)
Constant	-3.417*** (0.0848)	-3.436*** (0.0846)	-2.631*** (0.0853)	-3.473*** (0.0863)	-3.487*** (0.0860)	-2.647*** (0.0873)
inflate						
Constant	-0.819*** (0.0492)	-0.837*** (0.0499)	-1.103*** (0.0545)	-0.834*** (0.0503)	-0.849*** (0.0506)	-1.098*** (0.0541)
Observations	3399480	3399480	3146045	3399480	3399480	3146045

Table A.36: ZIP Results: Machine-Level, Minute & Smoothed Miniute Crowdedness: Standard errors are in parentheses and clustered at machine level. Machine, day-of-week, and timing fixed effects are controlled.

	(1)	(2)	(3)	(4)	(5)	(6)
temperature	0.0779*** (0.00293)	0.0781*** (0.00293)	0.0769*** (0.00300)	0.0783*** (0.00295)	0.0784*** (0.00295)	0.0771*** (0.00302)
precipitation	-0.00270*** (0.000359)	-0.00270*** (0.000360)	-0.00280*** (0.000369)	-0.00273*** (0.000361)	-0.00273*** (0.000362)	-0.00280*** (0.000369)
machine_PR	0.0756*** (0.00498)	0.0750*** (0.00508)	0.00742 (0.00586)	0.0734*** (0.00504)	0.0727*** (0.00511)	0.0124 (0.00661)
crowdedness_minute_1	0.00990*** (0.000575)	0.00974*** (0.000570)	0.00660*** (0.000451)			
departure	0.208*** (0.0100)			0.156*** (0.00874)		
machine_PR × crowdedness_minute_1	-0.000240 (0.000172)	-0.000292 (0.000176)	-0.000566** (0.000208)			
machine_PR × departure	-0.0700*** (0.00620)			-0.0553*** (0.00648)		
departure_next1		0.277*** (0.00914)			0.224*** (0.00839)	
machine_PR × departure_next1		-0.0662*** (0.00667)			-0.0518*** (0.00693)	
time to next			-0.0826*** (0.00245)			-0.0793*** (0.00233)
time to after next			-0.0600*** (0.00264)			-0.0570*** (0.00252)
machine_PR × time to next			0.0126*** (0.00135)			0.0119*** (0.00133)
machine_PR × time to after next			0.00318* (0.00130)			0.00269* (0.00131)
crowdedness_minute_2				0.0310*** (0.00227)	0.0300*** (0.00224)	0.0174*** (0.00185)
machine_PR × crowdedness_minute_2				-0.000877** (0.000304)	-0.000922** (0.000310)	-0.000775* (0.000311)
Constant	-3.518*** (0.0756)	-3.542*** (0.0754)	-2.731*** (0.0776)	-3.654*** (0.0770)	-3.669*** (0.0767)	-2.847*** (0.0798)
inflate						
Constant	-1.013*** (0.0469)	-1.035*** (0.0477)	-1.367*** (0.0545)	-1.061*** (0.0499)	-1.077*** (0.0503)	-1.377*** (0.0550)
Observations	3399480	3399480	3146045	3399480	3399480	3146045

Table A.37: ZIP Results: Machine-Level, Smoothed Minute Crowdedness, Machine x timing Fixed Effects: Standard errors are in parentheses and clustered at machine-level. Day-of-week and machine x timing fixed effects are controlled.

- Task 2: Buy a beverage at the vending machine near the mark for Car 5 on platform 7-8.
- Fill in the survey
- Fuchuu Honmachi Station
 - Task 3: Record the phone number written on the photo-taking machine on the concourse.
 - Task 4: Buy a beverage at the vending machine in front of Newdays store.
 - Fill in the survey
- Nishi Kokubunji Station
 - Task 5: Record the number of train toward Tachikawa on the train schedule between 8am and 9am.
 - Task 6: Buy a beverage at the vending machine near the mark for Car 6 on platform 2.
 - Fill in the survey
- Kunitachi Station
 - Exit and return to this room.

All participants receive basic participation compensation of 800 yen. In addition to this basic compensation, extra performance pay will be made depending on the time it takes to complete all the tasks. If a subject returns this room within 50 minutes, we pay extra 2500 yen. If it takes more than 50 minutes, 50 yen per minute of delay will be deducted from the 2500 yen performance pay. Moreover, any wrong answer on Tasks 1, 3, and 5 will result in 200 yen reduction in the performance pay. Failure to present the drinks you bought also results in 200 yen reduction in the performance pay.

B.2 Survey response sheet for the first manipulation check experiment. Responses to first question for Tasks 2, 4, and 6 corresponds to Q1 and second question to Q2 in Appendix A2.

- Name:
- Station at which the tasks are conducted:
- Time the task was started:
- Time to the next train:

Task 1

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

Task 2

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

Task 3

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

Task 4

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

Task 5

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

Task 6

1. Please rate the degree to which you are hurried out of ten, 0 being least hurried, an 10 being extremely hurried.
2. What is the extent to which you feel hurried? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.

B.3 Instruction for the second manipulation check experiment

The purpose of this experiment is to investigate the effects of other people in making a purchasing decision.

I form a group of two, three, and four right now. I would like each group to take a train from Kunitachi station to Tachikawa station, and then from Tachikawa station to Kunitachi station, making a beverage purchases at the vending machines specified below. Fill in the survey immediately after the tasks are completely in each station. In addition, take a memo observing

how other people make purchases as we will ask you to provide us with your observation after you return to this room.

- Kunitachi station
 - Buy ticket to Tachikawa station
 - Task 1: Buy a beverage at the vending machine on the platform toward Tachikawa station at the mark Car 6. If this vending machine is not available to make a purchase, buy a beverage at the vending machine on the same platform at the mark Car 4.
 - Fill in the survey

- Tachikawa station
 - Exit, and buy ticket to Kunitachi station
 - Task 2: Buy a beverage at the vending machine on the platform 3-4 at the mark Car 10. If this vending machine is not available to make a purchase, buy a beverage at the vending machine on platform 7-8 at the mark Car 5.
 - Fill in the survey

- Tachikawa station
 - Kunitachi station
 - Task 3: Buy a beverage at the vending machine on the platform toward Tokyo station at the mark Car 6. If this vending machine is not available to make a purchase, buy a beverage at the vending machine on the same platform at mark Car 5.
 - Fill in the survey
 - Exit, and return to this room

B.4 Survey response sheet for the second manipulation check experiment. Three sheets corresponding to Tasks 1, 2, and 3 are provided to the subjects. Response to the first question corresponds to Q3 and the second question to Q4 in Appendix A2.

- Name:
 - Station you make a purchase:
 - Number of people in your group:
 - How many people are around you (within 5 meters) at the time you make the purchase:
1. Please rate the degree to which you care about the people around you, 0 being not cared at all, and 10 being extremely extremely.
 2. What is the extent to which you care about other people around you? The answer is one of the following: 1 strongly disagree, 2 disagree, 3 neither agree nor disagree, 4 agree, 5 strongly agree.