At Your Service on the Table:
Impact of Tabletop Technology on Restaurant Performance

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Abstract

Some industries such as healthcare and financial services have reported significant productivity gains from introduction of new technologies. However, more traditional, labor-intensive industries are lagging behind. We use granular data to examine the impact of a customer-facing technology (a tabletop device that facilitates the table service process) on the check size and meal duration aspects of restaurant performance. The restaurant chain in our study implemented tabletop devices in a staggered manner, offering us a quasi-experimental setting in which to apply a difference-in-difference technique and identify the causal effect of the technology. We find that the tabletop technology is likely to improve average sales per check by 2.91% and reduce the meal duration by 9.74%, which increases the sales per minute or sales productivity by approximately 10.77%. Various robustness checks of our empirical strategy and post-hoc analyses find that efficient customers, who have lower cost of adopting new technology, generate more sales and have shorter meal duration than the inefficient customers do. Tabletop technology allows low-ability waiters to improve their performance more significantly than high-ability waiters. Overall, our results indicate great potential for introducing tabletop technology in a large service industry that currently lacks digitalization.

Keywords: technology innovation; self-service technology; labor productivity; restaurant operations, service operations

1 Introduction

Information technology has been found to be associated with higher productivity by reducing costs, increasing output quality, and intangible aspects such as convenience, timeliness and product variety in certain service sectors, including business services, financial services, and healthcare (Brynjolfsson and Hitt, 2000; Aral et al., 2012; Xue et al., 2011; Miller and Tucker, 2011; Hitt and Tambe, 2016; Bavafa et al., 2017). Still, many traditional service sectors remain largely undigitized or underinvested in technology (Gandhi et al., 2016) because of the intensive human aspects of the service process. Examples of non-digitized consumer activity include shopping at brick-and-mortar retailers, hiring house cleaners, checking in at a hotel front desk, and having a car serviced at repair shop (instead of buying parts online). Nevertheless, many traditional service sectors are starting to invest in technology to digitize (or "disrupt") their business models (Singh, 2015).

The restaurant industry is a case in point, though it seems to be one of the latecomers to technology innovation. Because of its people-intensive nature, restaurant managers focus on human aspects of services. Also, because of a low industry profit margin of between 1 and 7%, investing extra budget in technology innovation can seem hard to justify (Mogavero and A'agnese, 2016). While some novelties such as reservation systems (e.g., Opentable), delivery services (e.g., Uber Eats), and rating services (e.g., Yelp) are growing in popularity, what happens inside the restaurant with table service has remained largely unchanged for many years.

As one of the nation's major service sectors, the restaurant industry offers unique opportunities for technology innovation. In the United States, over one million restaurant locations generate more than $799 billion in annual sales, accounting for 4% of the nation's GDP. These restaurants hire 14 million workers (half of all adults have worked in the restaurant industry at some point during their lives) (NRA, 2017). In addition, restaurants offer an experiential service that can directly trigger customers' extreme happiness or displeasure. Two in five consumers report that restaurants are an essential part of their lives. Recognizing such opportunities, the restaurant industry has just recently begun to increase spending on technology-related initiatives (Lee et al., 2015). Industry reports estimate that the U.S. restaurant industry spent 5.8% of its revenues on technology in 2014, as compared to 3.5% in 2013 (Lorden and Pant, 2015). Restaurants are adopting technology in several aspects of the restaurant business (CBInsights, 2017), including review and search (e.g., Koshertopia, Foodspotting), reservations (e.g., Nowait, QLess), next-generation ordering/payment (e.g., Ziosk, E la Carte), loyalty and rewards (e.g., FiveStars, LevelUp), and HR analytics (e.g., ServeAnywhere, When I Work).

Implementing new technology incurs escalating costs to the already thin restaurant profit margin (Lee et al., 2015). In addition, restaurants (like other hospitality industries) traditionally have not realized the key advantages through technology that they have in location, decoration, and personnel. Human interaction is an integral part of restaurant hospitality, especially for full-service restaurants. Such interaction between customers and service-providers may be harmed by using self-serve technology (Schultze and Orlikowski, 2004). Although 20% of customers claim that they would rather use some kind of customer-facing technology than interact with restaurant staff, 45% feel that technology makes restaurant visits and ordering more complicated (NRA, 2017). Service-providers must devote extra effort to promote the technology and instruct customers to use it (Schultze and Orlikowski, 2004). Furthermore, technology that collects customer data may pose a significant risk of data breaches, damaging business performance (Baertlein, 2017). For these reasons, it remains unclear whether or not and how new technology may improve restaurant performance.

In this paper, we analyze more than 2.6 million transactions of a large, full-service casual restaurant chain as it implemented a customer-facing tabletop technology, to understand how the technology affects sales and meal duration aspects of restaurant performance. We study the full-service casual restaurants as our empirical setting because this sector is characterized by people-intensive table service. This sector of restaurants charge mid-range prices and collected over $90 billion revenues in 2014, qualifying it as economically significant. We focus on tabletop technology (see Section 2.2 for a detailed description of this technology) because industry executives are reported to prioritize customer-facing technology represented by the tabletop systems over other restaurant technology in order to enhance business efficiency and customer engagement (Lee et al., 2015). For our analysis, we exploit the staggered timing of the technology implementation and apply a difference-in-difference technique to identify the causal impact of tabletop systems on restaurant operations, followed by various robustness checks. In addition, we examine the nuances of the impacts that are oriented towards customers, waiters, and restaurant management, respectively. We find that tabletop technology is likely to improve average sales per check by 2.91% and reduce meal duration by approximately 9.74%, increasing the sales per minute or sales productivity by approximately 10.77%. We find that those customers who pay their checks with the tabletop device instead of with a waiter tend to spend more money and complete their meal in less time. In addition, consumer engagement level with the tabletop technology has a J-shaped relationship with spending and a reversed-J-shaped relationship with meal duration. That is to say, as consumers spend more time interacting with the device, from no interaction to a very long time using the device, their check size first slightly dips and then keeps rising, while their meal duration steadily shortens until it moderately lengthens. New technology helps reduce the performance gaps between high-ability waiters and low-ability waiters, in that the tabletop technology better increases sales and reduces meal duration for low-ability waiters than for high-ability ones. The new technology also helps waiters more effectively upsell and cross-sell.

Our research findings highlight the value of technology innovation for restaurant operations. We also generate insights for managers to reconsider changes in staffing decisions and the functions of the new systems to fully exploit the productivity gains from the new technology. Finally, our research suggests the importance of effectively managing the relationship with high-value technology-savvy customers.

2 Theoretical Background

2.1 Literature Review

We contribute to the ongoing research stream studying the impact of the information technology on firm/labor productivity (we refer readers to Tambe and Hitt (2012); Ren and Dewan (2015) for their excellent reviews of the literature concerned). IT investment is typically found to be associated with higher output, better output quality, and value for consumers, together with lower costs, thus increasing firm productivity (Brynjolfsson and Hitt, 1996; Hitt and Brynjolfsson, 1996; Brynjolfsson and Hitt, 2000, 2003). For its mechanism, on the one hand, research suggests that IT is a net substitute for both ordinary capital and labor input (Dewan and Min, 1997). On the other hand, research reveals that IT can complement workplace reorganization and new services to increase productivity (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000). Most of the research in this stream focused on firm-level (e.g., Brynjolfsson and Hitt (2000)) or country-level (e.g., Dewan and Kraemer (2000)) data, which provides generalizable evidence of the results. However, due to a general lack of data availability, little research was conducted using granular transaction data to reveal more information about how a technology specifically affects individual components in an applied service setting.

Only recently has a growing number of papers started to turn to granular level data to study the impact of technology on firm and labor productivity, like we do. For example, Aral et al. (2012) analyze detailed accounting records and email usage data, and find that electronic communication networks provide workers access to heterogeneous knowledge in a midsize executive recruiting firm, which helps them improve the matching of candidates and companies' requirements. Unlike Aral et al. (2012)'s paper, which studies an information-intensive business service company, our study analyzes a people-intensive hospitality firm where technology may affect firm and labor productivity through different mechanisms. In a closely related paper, Pierce et al. (2015) find that the implementation of a monitoring system (i.e., back-office technology) reduces employee theft and improves productivity in a casual restaurant setting. Our paper is differentiated from this work by two aspects: 1) we study a customer-facing technology that is reportedly attracting increasing interest from restaurant managers (Lee et al., 2015); and 2) the impact of our tabletop technology is jointly determined by customers' usage, workers' performance, and restaurants' labor decisions. By contrast, Pierce et al. (2015)'s paper focuses primarily on the workers' experience of the effect of the monitoring system.

Our paper also contributes to a stream of work about customer adoption of self-service technology. Many papers conduct surveys to study what attitudinal, behavioral, and demographic factors are associated with customers' decision to use self-service technology (see Campbell and Frei (2010); Susskind and Curry (2016) for an extensive review of the related literature). Only a handful of papers, including ours, use observational data to understand how self-service technology actually changes customer demand for service. In a series of papers analyzing online banking customer data, Xue et al. (2007) find that customers who choose to use the online banking channel tend to be more efficient in the service co-production process and tend to have higher profitability. Not only customer efficiency, but also customer demand for banking services, the availability of alternative channels, and local Internet banking penetration are all positively associated with the adoption of online banking (Xue et al., 2011). In addition, Campbell and Frei (2010) find that use of an online banking channel substitute the usage of ATMs and voice response units, augment service consumption at branch and call centers, and increase total transaction volume and average cost to serve, consequently reducing short-term customer profitability and improving long-term retention rates. Besides studies on financial services, healthcare is another active area examining the self-service technology use. For example, Rajan et al. (2013) theoretically show that adopting telemedicine will increase access to Parkinson specialists for patients who live longer distance, and therefore increase the number of patients treated. Similarly, Bavafa et al. (2017) empirically find that the introduction of an e-visit channel in a large health care system increases office visits by approximately 6%. Furthermore, Jerath et al. (2015) suggest that consumers tend to use the web portal (a self-service channel) of a health insurance firm to gain structured seasonal information and call the firm to receive health-related information. Xu et al. (2017) show how information from a new online doctor appointment booking platform, such as ratings, availability, and reviews, affect consumers' choice of doctors. These papers tend to focus on customer behavior changes because of new self-service technology. Our paper examines not only customer-oriented effects, but also worker-oriented and restaurant-oriented effects because the casual dining setting is differently characterized with high worker/consumer interaction intensity. In addition to empirical work, Gao and Su (2017) formulate an economic theory predicting that self-order technology should reduce customers' waiting time and increase demand in a quick-service restaurant setting (e.g., McDonald's). They consequently suggest that firms should implement self-order technology when consumers have high wait sensitivity. Our empirical work aims to test this theory prediction, although our empirical setting is a full-service casual restaurant rather than a quick-service restaurant.

Our paper uses restaurant operations as an empirical setting. Other empirical work on restaurant operations includes table capacity/mix/configuration design (Kimes and Thompson, 2004; Thompson, 2007), labor staffing and scheduling (Thompson, 2004; Tan and Netessine, 2014b,a, 2015), assigning of customers to waiters (Tan and Staats, 2017), theft prevention software (Pierce et al., 2015), waiting time cost (Allon et al., 2011), and food supply chain quality (Yu et al., 2017). Our research adds to this steam of literature by studying the impact of a novel customer-facing technology on restaurant performance.

To sum up, our paper makes three contributions to the literature. First, our research uses granular-level observational data to understand the impact of tabletop technology on firm and labor productivity in an applied setting. Second, we study a customer-facing technology that is attracting increasing interest in the restaurant industry, and industry that offers significant opportunity for growth in technology innovation. Third, we examine customer-oriented, worker-oriented, and restaurant-oriented effects of tabletop technology in a people-intensive service industry with close worker/consumer interaction.

2.2 Tabletop Technology

The tabletop technology that we study allows casual dining customers to view menu items, order food and beverages, and pay for the meal on the tablet device at the table. It also provides entertainment, such as games and news content. These functions can be adapted to restaurant-specific needs and requirements. Our focal restaurant chain was one of the first adopters of this technology in the early 2010's. It implemented the technology in order to assist its waiters, as opposed to replacing them. The device is placed on each table in the dining room. After being seated by the host, customers are greeted by a waiter, who presents the regular paper menu, takes the first drink orders, and introduces the tabletop technology to customers unfamiliar with it. Then customers choose to interact with the device at their own discretion. If they click on the "menu" tab, they will see food and beverage items with photos and text descriptions. The digital descriptions help customers make ordering decisions because they offer more detail than a paper menu can offer, due to its limited space. After the waiter returns to take orders, customers may ask the waiter for clarification and recommendations, and place the order of food and beverage with the waiter. While the device is capable of handling all orders, the restaurant chain requires waiters to take customers' food and first alcoholic beverage orders because 1) the restaurant regards waiter-customer interaction as a personalized service process (e.g., waiters are trained to help customers with food restrictions or allergies and customize the order accordingly); 2) alcoholic beverage orders require age verification. During the meal, customers may reorder alcoholic drinks directly from the tabletop device. In addition, customers can read digital news feeds for free on the tablet and play tablet-based games, such as trivia and chess, for a flat fee of 99 cents. When the customers are ready to pay, they can either pay with a waiter or pay with a credit card on the device without the presence of a waiter. After they receive a printed receipt from the tabletop device or select an option to receive it by email, customers see a green light signal, indicating that they may leave the restaurant.

2.3 Theoretical Prediction

The aforementioned literature helps us make a theoretical prediction about the impact of tabletop technology on restaurant performance. First, technology can complement workers by freeing up their capacity and providing them with more information, so that they can enhance their productivity (Brynjolfsson and Hitt, 2000; Hitt and Tambe, 2016). The tabletop technology in our study assists waiters in introducing menu items, reordering alcoholic drinks, entertaining customers, and receiving payments. These benefits can increase waiters' ability to conduct effective suggestive selling and provide customers with prompt service. Second, consumers may perceive more control in the service delivery process, as well as a shorter wait time, thus increasing their demand for service (Campbell and Frei, 2010; Susskind and Curry, 2016). In our setting, consumers can avoid waiting to get the attention of the waiter to reorder alcoholic drinks or pay for their meal (more details about the technology can be found in Section 2.2), which should save them time and make the dining experience more convenient and enjoyable. Consequently, consumers may decide to spend more money on the meal. Third, the shortened wait time for the consumers who use the self-order technology can further reduce the wait time of other consumers who do not use the technology, because the totality of customers contributes to congestion in the same service system (Gao and Su, 2017). For these reasons, we hypothesize that

HYPOTHESIS 1a: *Tabletop technology increases the sales for an average check, everything else being equal.*

HYPOTHESIS 1b: *Tabletop technology reduces the meal duration of an average check, everything else being equal.*

Service is a co-production process, so the effects of a new technology should be influenced by both customers and service providers (Roels, 2014; Karmarkar and Roels, 2015). From a customer's view point, learning how to use the new technology, which requires some degree of self-service, instead of relying on the traditional servers, incurs different "costs" for different customers. For example, a long-time customer of the service provider may be very familiar with the product and can understand where the new technology fits into the service process. In addition, a highly educated person generally would be expected to have a strong ability to learn new technology. Similarly, a technologically skilled customer may have both deep knowledge and curiosity to explore new technology. In other words, a customer's history with the company, education, and technology skills may all be associated with a lower cost of embracing new technology. These customers are referred to as "efficient customers" in the service co-production literature (Xue and Harker, 2002). Efficient customers require fewer resources because they tend to use self-service technology, which is generally faster and cheaper than traditional labor. They also generate more revenue because they are typically associated with longer tenure with the company, higher education levels, and technology skills. Hence, customer efficiency is found to be associated with higher customer profitability (Xue et al., 2007, 2011). Translating this theory into our empirical setting, we postulate that those customers who use tabletop technology are likely to have high customer efficiency. Therefore, we form the following hypotheses:

HYPOTHESIS 2a: *The customers who use tabletop technology (efficient customers) should generate more sales than those who do not use the tabletop technology (inefficient customers), everything else being equal.*

HYPOTHESIS 2b: *The customers who use tabletop technology (efficient customers) should have shorter meal duration than those who do not use the tabletop technology (inefficient customers), everything else being equal.*

In addition to the customer efficiency variable, the impact of new technology also depends on another variable – that of the service provider's (i.e., waiter's) skill level. New tabletop technology should improve the performance for every waiter because it complements waiters' responsibilities and effectively expands their capacity in terms of both sales ability and service speed (as explained in Hypothesis 1). However, waiters have varying innate ability levels (Tan and Netessine, 2015; Tan and Staats, 2017), so some may benefit from technology more than others. We anticipate that the technology is likely to help low-ability workers improve their performance more significantly than high-ability workers. First, the gained performance improvement from technology is less likely to duplicate what high-ability workers already deliver (Gray and MeGray, 2004). The performance improvement (output) should concavely increase in service quality provided (input), which is positively associated with a waiter's ability (e.g., Lu et al. (2017)). In other words, performance improvement may approach an asymptotic limit as the worker's ability increases. High-ability waiters may already offer the higher sales-generating superior service quality that the tabletop technology aims to complement. For example, a high-sales-ability waiter may vividly describe the menu items to develop customers' appetite. A high-speed-ability waiter may pay close attention to his/her customers and respond to their reorder needs promptly, thus not only reducing the meal duration but also generating extra sales (Tan and Netessine, 2015; Tan and Staats, 2017). Similarly, high-ability waiters may already provide more of the kind of prompt service that the tabletop technology is designed to facilitate. For instance, high-sales-ability waiters can anticipate customers' refill needs and may fill customers' glasses before they order through the tabletop. High-speed-ability waiters may also anticipate when customers may want to receive the check, streamlining the payment process. Tabletop devices aim to deliver the types of high performance services that high-ability waiters may already offer.

By contrast, there is a low probability that technology will duplicate performance boost for low-ability workers. Also, low-ability workers have a stronger need and inclination to turn to technology for help because they may feel social pressure to reduce their performance disparity with high-ability coworkers (Kandel and Lazear, 1992; Mas and Moretti, 2009; Roels and Su, 2013; Kuziemko et al., 2014). In other words, low-ability waiters may perceive greater benefits from tabletop technology than high-ability workers perceive, which may motivate the low-ability waiters to more proactively use the technology (Gatignon and Robertson, 1989; Iacovou et al., 1995; Chwelos et al., 2001). For example, low-ability waiters may more enthusiastically introduce the tabletop device to the customers than their high-ability coworkers may, to encourage customers to use the device. Encouraging the use of the tabletop technology should further maximize its performance boost.

For these reasons, we posit that

HYPOTHESIS 3a: *The tabletop technology increases the sales for low-ability waiters more significantly than for high-ability ones, everything else being equal.*

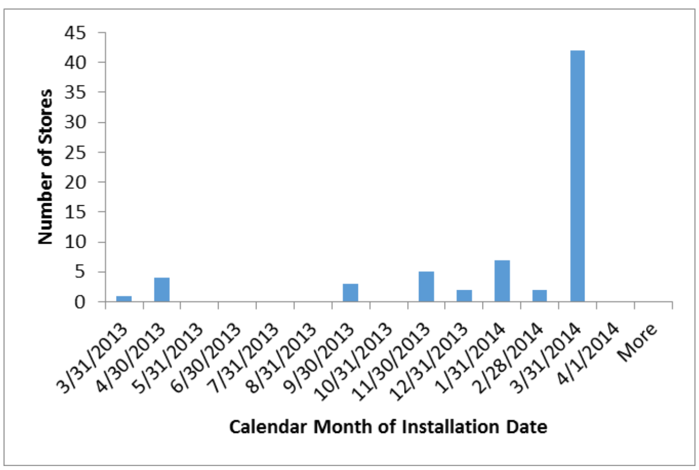
HYPOTHESIS 3b: *The tabletop technology increases service speed for low-ability waiters more significantly than for high-ability ones, everything else being equal.*

3 Empirical Strategy

3.1 Data

We collected the data directly from the restaurant chain on the conditions of anonymity and non-disclosure. Our sample includes all 66 restaurants of this chain in a major metropolitan area in the United States. The chain installed the tabletop technology in a staggered fashion from March 2013 to March 2014. Figure 1 shows the installation dates of the tabletop technology for each location in the data. As can be seen, the majority of the stores (42 stores) installed the tabletop systems in March 2014. The chain provided us with the data in three time periods: the first period ranges from December 2012 to February 2013, when none of the restaurants installed the tabletop technology; the second period ranges from December 2013 to February 2014, when 24 restaurants installed the tabletop systems (as part of the pilot stores, 11 out of these 24 restaurants installed the technology during this period of time); the last period ranges from May 2014 to July 2014, when the remaining restaurants installed the tabletop technology. Ideally, we would have liked to obtain the continuous observations from December 2012 to July 2014. Due to the company's sensitivity, we were only able to collect the three periods of data. Fortunately, the three time periods cover various stages of the technology adoption (i.e., pre-adoption, adoption, post-adoption)[1]. In addition, there was a significant variation in installation dates. The staggered installation dates and our three observation periods offered the benefit of allowing us to disentangle the effects of adopting the tabletop technology on the restaurant performance from other confounding factors (more details will be provided in Subsection 3.2).

Figure 1: Histogram of Installation Months



Our analysis focuses on the main dining room data because 1) the dining room is typically the largest source of restaurant sales and 2) it operates differently from the bar or the to-go orders counter. The to-go order counter served as a placebo test, on which we will elaborate in Subsection 4.2.3. Furthermore, we

[1] As a robustness check, we focused on one wave of introduction between December 2013 and February 2014 (period II) to create a direct pre-installation and post-installation comparison between the treatment restaurants and the control restaurants. During this period, all the restaurants that introduced the tabletop devices in March 2014 (the last wave) were still the control restaurants (42 in total). We also excluded the handful restaurants that implemented the devices before December 2013 from our sample (13 in total). Finally, we analyzed all the observations during period II, and found that the results were consistent with our main results both qualitatively and quantitatively. Focusing on one continuous period provides a classic difference-in-difference setting and corroborates our main results.

eliminate the top 5% and bottom 5% of daily transactions to reduce the influence of outliers (e.g., very large parties and private events). The final data includes slightly over 2.6 million check-level observations of the sales, items sold, check opening and closing times, the waiter associated with the check, party size, and tips. In addition, we record the dates when the tabletop technology was implemented.

Table 1 shows the summary statistics of the check-level data in the three periods. These statistics provide a preliminary glimpse into the change in restaurant performance due to tabletop technology implementation. For example, the average sales per check increases from \$30.45 during period I to \$31.82 during period III. The average meal duration drops from 55.3 minutes during period I to 49.76 minutes during period III. These basic performance data are in line with those reported in other restaurant revenue management studies (Kimes and Thompson, 2004; Kimes and Robson, 2004). Furthermore, the average number of items sold increases from 5.02 during period I, when only food, beverages, and alcoholic drinks are sold, to 5.3 during period III, when an additional flat-rate game option is sold on the tabletop systems. In addition, both food and alcoholic drinks sold increase from 3.33 and 0.42, respectively during period I to 3.43 and 0.46, respectively during period III. Besides these performance-related variables, the average party size grows slightly from 1.97 people in period I to 2.05 people in period III. In terms of the customers' adoption of the new system, 14% of the checks were paid via the new tabletop technology in the entire sample during period II (when 24 restaurants had the systems installed), and 60% were paid during period III (when all 66 restaurants had the systems installed). On a scale between zero (null) and four (very high), the average customer/tabletop engagement level rises from 0.611 during period II to 2.88 during period III.

Preliminary as these results are, they offer model-free evidence of the effects that we seek to demonstrate using a more rigorous identification strategy to delineate the effect of tabletop technology on restaurant performance.

Finally, before we delve into our empirical strategy, we examine the correlation matrix of the check-level variables as sanity checks (see Table 2). As expected, *Sales* is positively correlated with *MealDuration* (0.2529), the variables representing the number of item sold (i.e., *ItemNum* (0.9088), *FoodNum* (0.8238),

Table 1: Summary Statistics of Check-level Observations

	Definition	Period 1 (12/2012 - 2/2013) Mean	SD	Period II (12/2013 - 2/2014) Mean	SD	Period III (5/2014 - 7/2014) Mean	SD
Sales	Sales per check in dollars	30.45	15.46	31.59	16.13	31.82	16.06
MealDuration	Length of a meal in minutes	55.30	20.80	54.04	20.22	49.76	18.91
ItemNum	Number of items sold	5.02	2.65	5.08	2.69	5.30	2.84
FoodINum	Number of food items sold	3.33	1.77	3.35	1.77	3.43	1.85
BeverageNum	Number of beverage items sold	1.29	1.14	1.27	1.13	1.26	1.13
AlcoholNum	Number of alcoholic drink items sold	0.42	1.36	0.44	1.39	0.46	1.39
PartySize	Number of customers in a party	1.97	1.03	2.00	1.03	2.05	1.07
SystemPayment	Binary variable (zero and one) indicating if the check is paid with the tabletop technology	0	0	0.14	0.35	0.60	0.49
EngagementLevel[1]	Categorical variable (zero, one, two, three, four) indicating users' null, low, medium, high and very high engagement levels with the tabletop system, respectively.	0	0	0.61	1.19	2.88	1.05
Observations		896,825		851,081		862,624	

[1] : The engagement level is defined by the system provider in terms of engagement duration, whose exact definitions are unavailable to the researchers.

BeverageNum (0.4625)*, AlcoholNum* (0.3537)), and *PartySize* (0.7434). *MealDuration* is also positively correlated with those variables related to the number of item sold (0.2207, 0.2044, 0.0296, 0.1698, respectively) and *PartySize* (0.1420). Among the breakdown of the types of the items sold, *FoodNum* positively correlates with *BeverageNum* (0.4128) and *AlcoholNum* (0.0988), implying that beverages and alcoholic drinks are generally complements to food items. However, beverages and alcoholic drinks tend to be substitutes to each other because the correlation between *BeverageNum* and *AlcoholNum* is negative (-0.1854). All of these correlations match our expectations, which suggests that the data passes the sanity check. We proceed with our identification strategy in the next section.

Table 2: Check-level Correlation Matrix

	Sales	*MealDuration*	*ItemNum*	*FoodNum*	*BeverageNum*	*AlcoholNum*
Sales	1.0000					
MealDuration	0.2529*	1.0000				
ItemNum	0.9088*	0.2207*	1.0000			
FoodNum	0.8238*	0.2044*	0.8946*	1.0000		
BeverageNum	0.4625*	0.0296*	0.6152*	0.4128*	1.0000	
AlcoholNum	0.3537*	0.1698*	0.2663*	0.0988*	-0.1854*	1.0000
PartySize	0.7434*	0.1420*	0.6520*	0.6564*	0.4169*	0.0590*

*: Significant at the 0.05 level

3.2 Identification Strategy

In order to study the effect of tabletop technology on restaurant performance, we employ a difference-in-difference (DID) strategy. We consider the tabletop system implementation as a "treatment" on a restaurant, while using the pre-implementation restaurants as the control group. The DID strategy estimates the change in the performance difference between the treated restaurants and the control after the treatment, which in effect distinguishes the true effect of the system implementation from the factors that may affect the performance of both treated and control restaurants (e.g., menu item change, economy factors) over time. In other words, the control restaurants are used as counterfactuals for how performance would have changed in those treated restaurants if they had not installed the systems. DID is a valuable econometric technique for evaluation of the impact of policy in social sciences (e.g., Card and Krueger, 2000), and has been successfully used to study Operations Management related issues (Pierce et al., 2015; Lu and Lu, 2016; Staats et al., 2016).

To pursue our DID strategy, we employ the following models to estimate the effect of tabletop technology on performance in terms of sales and meal duration at the check level, respectively:

$$\log(Sales_i) = \alpha_0 + \alpha_1 System_i + \alpha_2 \log(MealDuration_i) + \alpha_3 PartySize_i + \alpha_4 Controls_i + \varepsilon_i \tag{1}$$

$$\log(MealDuration_i) = \beta_0 + \beta_1 System_i + \beta_2 \log(Sales_i) + \beta_3 PartySize_i + \beta_4 Controls_i + \xi_i \tag{2}$$

$$\log(Sales_i/MealDuration_i) = \gamma_0 + \gamma_1 Systems_i + \gamma_2 PartySize_i + \gamma_3 Controls_i + \theta_i \tag{3}$$

In these models, we log-transform the dependent variables, which is a commonly used technique (Albright and Winston, 2014), to make the residuals more symmetrically distributed to form a bell shape for inference purposes. We focus on sales, meal duration, and sales per minute as our main performance measures because 1) sales is an integral performance measure in the casual dining industry, where profit margins are only 1% to 7%; 2) meal duration is related to service speed; and 3) sales per minute reflects sales productivity.[2] We consider a break-down of the number of items sold in terms of food, beverages, and alcoholic drink items in Section 4.4 as additional analysis to show the insights about the tabletop technology impact.

On the right-hand side of the models, *System* is a binary variable, which is equal to one when check i happened after the restaurant implemented the tabletop system, and zero otherwise. Its coefficient will assess the impact of the system on the restaurant performance. In addition, we control for the meal duration in the sales model (Model 1), and vice versa (Model 2) because sales is typically positively associated with meal duration. In all three models, we further control for *PartySize* and a group of other *Controls* variables that include the fixed effects of the working shift (lunch or dinner), the day of the week, the weekly trend, and the stores. These additional categorical variables in the *Controls* adjust for the drivers of the restaurant performance variation, such as intra-day demand, trend, seasonality, and neighborhood-specific factors, which are all unrelated to the implementation of tabletop technology, and they have been used extensively in the literature that references restaurant data. We then use ordinary least squares (OLS) regressions to estimate all the models, and calculate heteroscedasticity-consistent standard errors to allow the fitting of our model to contain potential heteroscedastic residuals.

[2]Although tips ratio can reflect service quality and customer satisfaction, we find that this effect on tips ratio is not only statistically insignificant but also rather small in magnitude probably because customers are accustomed to tipping at a fixed percentage as a social norm in the United States. Therefore, we decided to focus on the effect of tabletop technology on sales and meal duration. Similar result is reported in Tan and Netessine (2014b).

4 Results

4.1 Treatment Effects

Table 3 shows the treatment effects of tabletop technology on the restaurant performance. The coefficient of *System* is statistically significant and positive in the sales model (0.0291), suggesting that the tabletop technology may increase average sales per check by 2.91% (or approximately \$0.88 of the average check size of \$30.45 during period I), controlling for everything else. This 2.91% increase is practically significant, given the low-margin nature of the casual dining business. In addition, Column 2 shows that the coefficient of *System* is statistically significant and equals -0.0974, suggesting that the tabletop system may reduce the meal duration by 9.74% (or approximately 5.38 minutes of the average pre-installation meal duration of 55.3 minutes), everything else being equal. Note that this 9.74% meal duration reduction can primarily be associated with more efficient service, as opposed to a lower number of ordered items, because we control for the sales in the model. With increased sales and shorter meal duration per check, Column 3 shows that tabletop technology is estimated to increase sales productivity by 10.77%, which implies that the sales productivity may increase from (\$30.45/55.3 minutes = \$0.55/minute) in period I to \$0.61/minute.

Furthermore, the coefficients of the control variables demonstrate associations in expected directions. For example, the coefficient of log(*MealDuration*) is 0.1927 in the sales model, while the coefficient of log(*Sales*) is equal to 0.1857 in the meal duration model, implying that sales and meal duration are positively associated with each other. Finally, *PartySize* is positively associated with larger check size and longer meal duration, matching expectations.

4.2 Robustness Checks of Internal Validity

4.2.1 Parallel Trends Assumption

The validity of the DID technique relies on a critical assumption, that of parallel trends, which states that the treated and the control restaurants would have followed similar performance trends without the system

Table 3: Check-level Impact of Tabletop Technology on Restaurant Performance

	(1) log(*Sales*)	(2) log(*MealDuration*)	(3) log(*Sales/MealDuration*)
System	0.0291***	-0.0974***	0.1077***
	(0.0022)	(0.0060)	(0.0063)
log(*Sales*)		0.1857***	
		(0.0023)	
log(*MealDuration*)	0.1927***		
	(0.0030)		
PartySize	0.3154***	0.0548***	0.2735***
	(0.0017)	(0.0005)	(0.0018)
Controls	Yes	Yes	Yes
H1 Supported	Yes	Yes	Yes
Observations	2,610,530	2,610,530	2,610,530
Prob>Chi-sq	<0.001	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

implementation. We validate this assumption by 1) providing institutional knowledge of the restaurants, 2) conducting visual checks of the graphical trends of sales and meal duration, and 3) performing statistical tests of implementation timing decisions.

Our institutional knowledge of the restaurants supports the parallel trends assumption for the following three reasons. First, all of the restaurants in our sample belong to an established chain that operates with a uniformly similar management style. Second, the restaurants are all located in the same metropolitan area, thus making geolocational trends comparable across the restaurants. Third, the restaurants represent the entire population of this chain in the metropolitan area, which alleviates the potential selection bias of observing only a subset of restaurants that implemented the system.

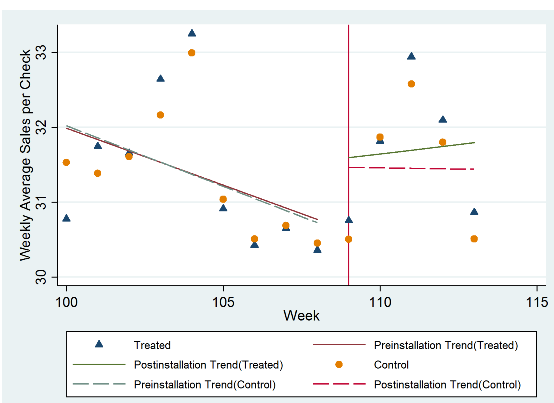
In addition to institutional knowledge, we illustrate the parallel trends before and after the implementation with two graphs of weekly average sales and weekly average meal duration, respectively, for the treated restaurants and the control group. For illustration purposes, we focus on the period from December, 2013 to February, 2014 (i.e., period II), when seven restaurants (defined as the treatment group) installed the tabletop systems during the same week in January (109th week in our sample) (defined as the treatment group), and 42 restaurants did not yet have the systems installed (defined as the control group). We examine one treatment timing (i.e., 109th week), excluding the 13 restaurants that implemented the systems before

December, 2013, two in December, 2013, and two in February, 2014.

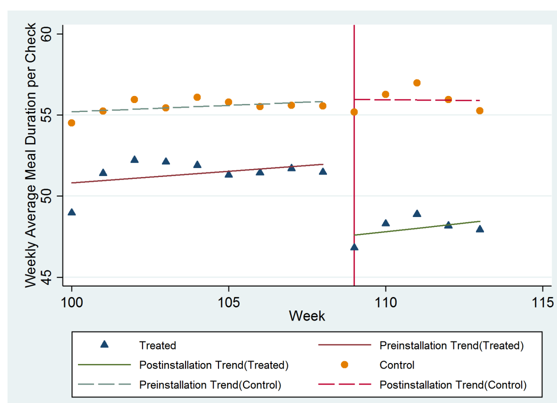
Figure 2a shows the weekly average sales per check of both the treated and the control groups before and after the 109th week when seven restaurants installed the tabletop technology (represented by a vertical line). The treated and the control restaurants seem to have almost identical linearly-fitted downward trends before the installation week. After the installation week, however, the treated group begins an upward trend, while the control group continues a slightly downward trend. In addition, the treated group begins to show a higher level of average sales per check than the control group. Figure 2b further illustrates the weekly average meal duration of both the treated and the control groups before and after the installation week. Before the installation week, both the treated and the control groups have similar constant linearly fitted trends of average meal duration, although the control group tends to persistently show a longer meal duration than the treated group. However, after the installation week, the treated group shows a sharp drop in the level of its trend, whereas the control group continues its pre-installation trend with almost no change. In sum, both figures provide visual checks of the parallel trends assumption that states that the treated and the control groups have similar trends before the installation of the tabletop technology.

Figure 2: Visual Checks of Parallel Trends

(a) Weekly Average Sales per Check before and after the Week of January 27th, 2014



(b) Weekly Average Meal Duration per Check before and after the Week of January 27th, 2014



Finally, we perform two statistical tests to further support the validity of this assumption. First, we follow the approach of Pierce et al. (2015) by adjusting for separate weekly time trend dummies for treated and untreated restaurants in Models 1 to 2. In other words, we introduce the interaction between the weekly trend categorical variable and *System.* For the second, we regress the installation dates (a continuous variable of daily trends with a larger number indicating a later date) on the pre-installation average sales and meal duration per check in the 66 restaurants to determine whether or not there is a systematic bias towards the installation dates (i.e., endogenous treatment timing).

Table 4a presents the results of Models 1 and 2, controlling for different weekly trends at the treated and the untreated restaurants. The results are both qualitatively and quantitatively consistent with the main results in Table 3. Furthermore, Table 4b shows the results of the regression of installation dates on the pre-installation performance. Both coefficients are statistically insignificant, suggesting that pre-installation performance seems to be uncorrelated with the installation timing, a finding that seems to suggest that the timing of the system implementation is likely to be non-strategic. In addition, the R^2s are quite low (0.02 and 0.008), which further implies that the pre-installation performance cannot explain the variation in the installation dates.

Table 4: Parallel Trends Assumption Check

(a) Controlling for Weekly Trends for the Treated and the Untreated

	log(*Sales*)	log(*MealDuration*)
System	0.0274***	-0.0983***
	(0.0056)	(0.0080)
log(*Sales*)		0.1857***
		(0.0023)
log(*MealDuration*)	0.1917***	
	(0.0030)	
PartySize	0.3180***	-0.0057***
	(0.0017)	(0.0008)
Controls†	Yes	Yes
Observations	2,609,692	2,609,692
Prob>Chi-sq	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

†: weekly FEs×*System* instead of weekly FEs alone.

(b) Pre-installation Performance and Implementation Dates

	Installation Date	Installation Date
Pre-installation Average Sales per Check	12.1888	
	(10.5846)	
pre-installation Average Meal Duration		-2.3887
		(3.4338)
Observations	66	66
R^2	0.020	0.008

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

4.2.2 Persistent Effects

A potential confounding factor of the true effect of technology implementation on organization performance is the Hawthorne effect, which causes a temporary change in performance because of workers' awareness of being observed (Landsberger, 1957). When the tabletop technology was implemented, workers could have altered their behavior due to the attention of the management. In order to tease out the potential Hawthorne effect, we estimate individual treatment effects in each of the first eight weeks after the system was implemented to show the long-term effect of the tabletop technology. In other words, we replace *System* with eight dummy variables indicating each of the first eight weeks after the system implementation, while keeping the control variables the same as in Models 1 and 2.

The results are shown in Table 5. We observe that both sales and meal duration effects are likely to be persistent because the signs of the coefficients are statistically significant and consistent with the main results. In particular, the sales effects seem to significantly rise the fourth week after the system installation as the coefficient of week 4 increases by 62% from week 3 (to 0.0319 from 0.0196). The meal duration effects also seem to strengthen over time (the coefficient during week 1 is -0.0869, while the coefficient during week 8 is -0.0998). The increasing coefficient sizes alleviate the concern of a potential Hawthorne effect, which would have otherwise implied decreasing coefficients. In addition, the strengthening of the technology effects may imply that it takes time for organizations to learn how to properly maximize the value of new technology.

4.2.3 Placebo Tests

In order to alleviate the concern of finding false-positive results in our study (Bertrand et al., 2002), we conducted two types of placebo tests. In the first type of placebo tests, we followed the approach suggested in Pierce et al. (2015) and randomly assigned the actual implementation dates of the tabletop technology to the 66 restaurants, re-fitting our Models 1 and 2 60 times. In the second placebo test, we collected the POS data from the to-go orders of these restaurants. The to-go orders did not utilize the tabletop technology, so

Table 5: Persistent Effects

	log(*Sales*)	log(*MealDuration*)
Installation week 1	0.0169**	-0.0869***
	(0.0057)	(0.0092)
Installation week 2	0.0198***	-0.0716***
	(0.0044)	(0.0098)
Installation week 3	0.0196***	-0.0813***
	(0.0036)	(0.0105)
Installation week 4	0.0319***	-0.0862***
	(0.0068)	(0.0153)
Installation week 5	0.0418***	-0.0930***
	(0.0069)	(0.0170)
Installation week 6	0.0334***	-0.0967***
	(0.0070)	(0.0169)
Installation week 7	0.0278***	-0.0921***
	(0.0072)	(0.0159)
Installation week 8	0.0366***	-0.0998***
	(0.0076)	(0.0154)
PartySize	0.3185***	-0.0075***
	(0.0018)	(0.0007)
log(*Sales*)		0.1880***
		(0.0022)
log(*MealDuration*)	0.1953***	
	(0.0032)	
Controls	Yes	Yes
Observations	1,762,692	1,762,692
Prob>Chi-sq	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

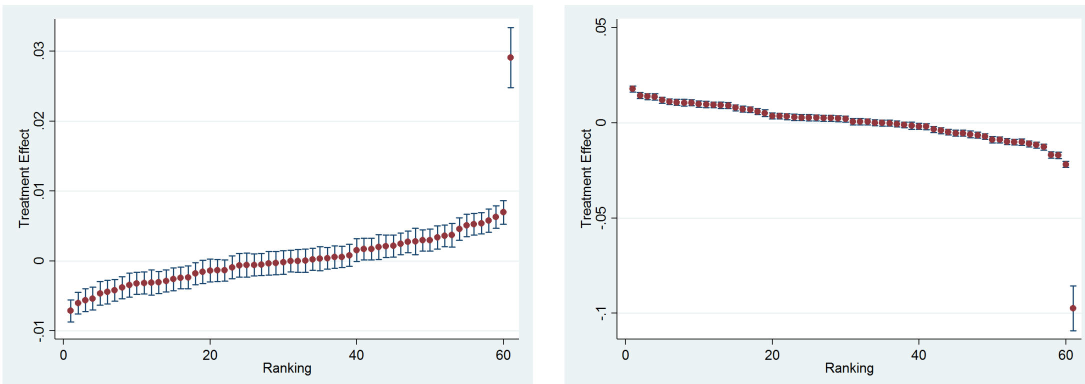
we expected the coefficient of *System* to be insignificant in our data analysis.

Figures 3a and 3b show the results of the first type of placebo tests of sales and meal duration, respectively. Each point is the estimate of the coefficient of *System,* while the capped spikes are their 95% confidence intervals. The 60 placebo point estimates are then ranked together with the actual estimate. In the sales model (Figure 3a), the placebo point estimates are capped between ± 0.01, while the actual estimate is close to 0.03 (more than three times as big as the largest placebo estimate). In addition, in the meal duration model (Figure 3b), the placebo point estimates are capped between ± 0.025, whereas the actual estimate is close to -0.1 (more than four times lower than the smallest placebo estimate). These wide differences between the placebo estimates and the actual ones alleviate the concern of spurious estimation because of the structure of our data sample. Furthermore, the coefficient of *System* in the to-go sample data (i.e., our second placebo test) is statistically insignificant, which further supports that our actual estimates will capture the main effects of the tabletop technology.

Figure 3: Placebo Tests

(a) Placebo Tests of the Effects of Tabletop Installation on Sales

(b) Placebo Tests of the Effects of Tabletop Installation on Sales



4.2.4 Hour-level Analysis

In addition to the check-level analysis, we conducted an analysis at the hourly level. This aggregate level analysis not only provides a robustness check for the check-level analysis, but also shows the impact of tabletop technology on the total sales when we control for the total traffic (additional analysis on the effect of traffic will be provided in Section 4.5.2). Specifically, we employ the following hour-level models:

$$\log(HrAvgSales_{rh}) = \alpha_0 + \alpha_1 Software_{rh} + \alpha_2 \log(HrAvgMealDuration_{rh}) + \alpha_3 HrAvgPartySize_{rh} + \alpha_4 \log(HrTables_{rh}) + \alpha_5 Controls_{rh} + \varepsilon_{rh} \tag{4}$$

$$\log(HrAvgMealDuration_{rh}) = \beta_0 + \beta_1 Software_{rh} + \beta_2 \log(HrAvgSales_{rh}) + \beta_3 HrAvgPartySize_{rh} + \beta_4 \log(HrTables_{rh}) + \beta_5 Controls_{rh} + \gamma_{rh}, \tag{5}$$

where $HrAvgSales_{rh}$ and $HrAvgMealDuration_{rh}$ represent the hourly average sales and meal duration per check during hour h at restaurant r. In addition, $HrAvgPartySize_{rh}$ and $HrTables_{rh}$ are, respectively, the hourly average party size per check and the number of tables that opened the check during hour h at restaurant r (a measure of restaurant traffic). *Controls* include the same set of temporal and locational categorical control variables as in Model 1, which are the fixed effects of shifts, the day of the week, the weekly trends, and the stores.

Table 6 shows the results of the hour-level analysis. As with the check-level results, the coefficient of *System* for sales is significant and positive (0.0284), while its coefficient for meal duration is significant and negative (-0.0904). In addition, the magnitudes of these two coefficients are in the range of the check-level results, which suggest that tabletop technology is likely to improve average sales by close to 3% and reduce meal duration by close to 10%, controlling for restaurant traffic and other factors. When the traffic is adjusted for, the impact on the average sales per check can also be interpreted as the impact on total sales. Finally, we repeat our analysis at the daily and weekly levels and find qualitatively and quantitatively consistent results.

Table 6: Hour-level Analysis of the Impact of Tabletop Technology on Restaurant Performance

	log(*HrAvgSales*)	log(*HrAvgMealDuration*)
System	0.0284***	-0.0904***
	(0.0039)	(0.0064)
log(*HrAvgSales*)		0.1985***
		(0.0027)
log(*HrAvgMealDuration*)	0.2634***	
	(0.0048)	
HrAvgPartySize	0.3499***	-0.0090***
	(0.0021)	(0.0019)
log(*HrTables*)	0.0147***	0.0478***
	(0.0022)	(0.0019)
Controls	Yes	Yes
Observations	215,527	215,527
Prob>Chi-sq	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

4.3 Consumer-Oriented Impacts

In order to examine H2 in our restaurant setting, we characterize high customer efficiency as the active use of the new tabletop technology because 1) the device is installed at every table and 2) waiters cannot discourage customers from using the device. The precise clickstream usage data are unavailable in our data set, so we use two types of proxies for the customer efficiency. First, we analyze the data on whether a customer used the tabletop device to pay at the table or paid using the traditional POS system with a waiter. We use this data to capture the usage of the device because the payment function is one of the major technological innovations introduced by the tabletop devices. Second, we use the recorded engagement level with the tabletop technology as an alternative measure of customer efficiency. In particular, we estimate the following models:

$$\log(Sales_i) = \alpha_0 + \alpha_1 System_i \times CustomerEfficiency_i + \alpha_2 \log(MealDuration_i) + \alpha_3 PartySize_i + \alpha_4 Controls_i + \varepsilon_i \quad (6)$$

$$\log(MealDuration_i) = \beta_0 + \beta_1 System_i \times CustomerEfficiency_i + \beta_2 \log(Sales_i) + \beta_3 PartySize_i + \beta_4 Controls_i + \xi_i, \quad (7)$$

where *CustomerEfficiency* is first operationalized as the dummy variable, indicating whether a check is paid with the tabletop device or the traditional POS, and then alternatively defined as the categorical variable representing the engagement level with the device (i.e., non-user, low, medium, high, very high), which depends on the duration of the interaction with the device.[3] In addition, before the system is implemented, all customers pay their checks via POS and are considered non-users in the engagement level measure.

Figures 4a and 4b illustrate the results of the moderating effects by payment methods. In support of H2, the customers who choose to pay their checks via the tabletop devices (57% of the population) spend 8.29% more money and 22.97% less time than those who pay their checks via the traditional POS system (43% of the population). In addition, those customers who still pay via the POS (i.e., less efficient customers) generate lower sales and stay longer at the table after the tabletop implementation than before. These less efficient customers may be low spenders, which is consistent with theory suggested by Xue et al. (2007).

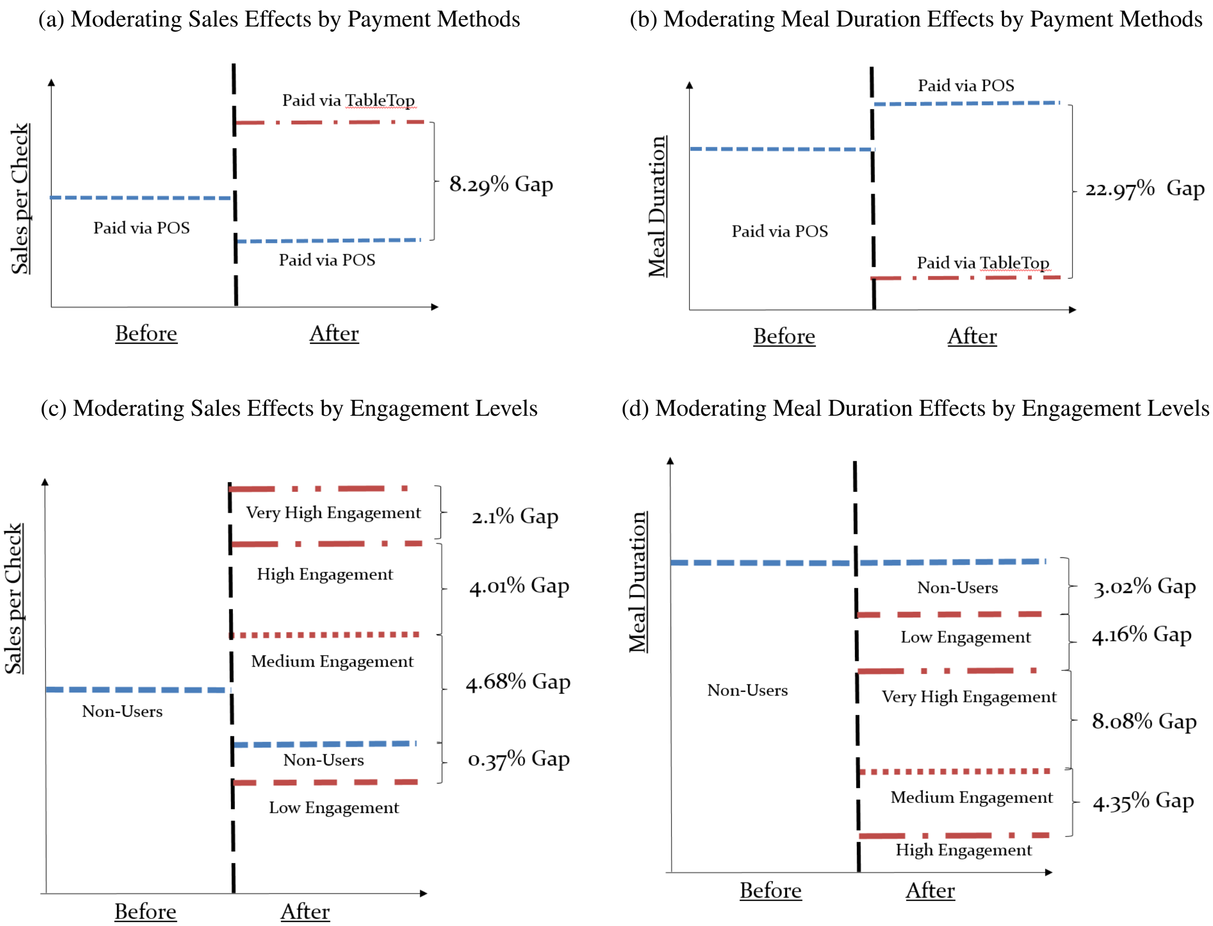
Figures 4c and 4d show the results of the moderating effects by engagement levels. For sales, the highest spenders are those customers that have "very high" engagement level with the device (32.2% of the popu-

[3]These data are coded by the device manufacturer and represent the duration of the interaction. The exact definition of these levels are unavailable to the authors.

lation), who may use the device to reorder alcoholic drinks and buy games. These highest spenders spend on average 2.1% more than the second highest spenders, who have a "high" engagement level (31.67% of the population). These "high" engagement level customers then spend on average 4.01% more than the customers, who have a "medium" engagement level (19.17% of the population). These three groups all spend more than the pre-installation average. However, those who choose not to touch the device at all (i.e., non-users, 1.62% of the population) spend less than the pre-installation average. Similarly, those customers who have a "low" engagement level (15.34% of the population) also spend less than the pre-installation average, and 0.37 less than the non-users. These non-users or "low" engagement users are also likely to be less efficient customers probably because they will not or cannot use the new technology. In summary, these results seem to exhibit a J-shaped relationship between customers' engagement level with the new technology and their spending, and support our H2a that states that the customers who use tabletop technology (efficient customers) generally generate more sales than those who do not use the tabletop technology (inefficient customers).

For meal duration, the fastest customers are also those who have a "high" engagement level with the device. They may use the device to reorder drinks without waiting to catch the waiter's attention and later pay their checks at the table. These fastest customers spend on average 4.35% less time than the second fastest group, who have a "medium" engagement level. The "medium" engagement customers are actually 8.08% faster than the "very high" engagement customers. They may read the news and play with the games at the tabletop device, which takes extra time. The "low" engagement customers and "non-users" spend an even longer time at the table, probably because they rely on the waiters, who simultaneously serve several other tables and take additional time to respond to customers. In addition, the meal duration of the "non-users" is statistically undifferentiable from pre-installation average, which implies that meal duration becomes shorter for most groups of customers after the implementation of the system. In sum, the moderating meal duration effects by engagement level seem to illustrate a reversed J-shaped relationship, which supports our H2b that predicts that customers who use tabletop technology (efficient customers) generally have shorter meal duration than those who do not use tabletop technology (inefficient customers).

Figure 4: Consumer-Oriented Impacts



4.4 Waiter-Oriented Impacts

In order to test our H3, we categorize waiters' skill levels by sales ability and speed ability because we primarily focus on sales and meal duration impacts in this paper. We first estimate the following fixed-effects models to estimate waiters' sales and speed abilities, respectively (similar models are used in Mas and Moretti (2009); Tan and Netessine (2015)):

$$\log(HrAvgSales_{jt}) = \alpha_0 + \alpha_1 \log(HrMealDuration_{jt}) + \alpha_2 AvgPartySize_{jt} + \alpha_3 Controls_{jt} + SalesSkill_j + \varepsilon_{jt}$$

$$\log(HrMealDuration_{jt}) = \beta_0 + \beta_1 \log(HrAvgSales_{jt}) + \beta_2 AvgPartySize_{jt} + \beta_3 Controls_{jt} + SpeedSkill_j + \xi_{jt}.$$

In these models, $HrAvgSales_{jt}$ and $HrMealDuration_{jt}$ are the hourly average sales and meal duration per check for waiter *j* during hour *t,* while $AvgPartySize_{jt}$ is the average party size of waiter *j* during the same hour *t*. The control variables $Controls_{jt}$ are the same as in Models 1 and 2. We estimate nine pairs of fixed effects for $SalesSkill_j$ and $SpeedSkill_j$ during each of the nine months in our study period to adjust for possible learning and forgetting effects on skills (Argote and Epple, 1990; Lapré et al., 2000; Shafer et al., 2001). Then we rank these skill levels and define the best 50% of the waiters in terms of *SalesSkill* and *SpeedSkill* every month as *HighSalesSkill* and *HighSpeedSkill,* respectively. Note a waiter with a high *SalesSkill* value and a low *SpeedSkill* value is considered to possess a high skill level.

After that, we adapt our main models to examine the moderating effects of waiters' skill levels:

$$\log(Sales_i) = \alpha_0 + \alpha_1 System_i \times SkillLevelType_i + \alpha_2 \log(MealDuration_i) + \alpha_3 PartySize_i + \alpha_4 Controls_i + \varepsilon_i$$

$$\log(MealDuration_i) = \beta_0 + \beta_1 System_i \times SkillLevelType_i + \beta_2 \log(Sales_i) + \beta_3 PartySize_i + \beta_4 Controls_i + \xi_i,$$

where we replace $SkillLevelType_i$, the ability type of the waiter associated with check *i* with dummy variables $HighSalesSkill_j$ and $HighSpeedSkill_j$, separately.

Table 7 shows the results of the moderating effects by waiters' skill types. In both sales models (Columns 1 and 3), the coefficients of *System* are significant and positive (0.0347 and 0.0401), while the coefficients of the interaction terms are significant and negative (-0.0131 and -0.0198). Interpreting the coefficients (summarized in Table 8), tabletop technology is likely to improve sales performance for low-sales-ability waiters by 3.47%, a value that is 1.31% higher than for the high-sales-ability waiters (2.16%), and for the low speed ability waiters by 4.01%, 1.98% higher than for the high speed ability waiters (2.03%), controlling for everything else. Alternatively, using the mean sales per check for these waiters before the implementation of the tabletop technology to interpret the absolute effect sizes, we find that the technology is likely to increase the sales performance for low-sales-ability waiters by ($3.47\% \times \$29.7 \approx \$1.03$), \$0.34 more for the high-sales-ability waiters ($2.16\% \times \$31.99 \approx \$0.69$), and for the low-speed-ability waiters by ($4.01\% \times \$31.05 \approx \$1.24$), \$0.62 more for the high-speed-ability waiters ($2.03\% \times \$30.7 \approx \$0.62$). Both the differences (\$0.34 and \$0.62) between the high- and low-ability workers are statistically significant.

These results suggest that the new technology is likely to increase the sales performance for both high- and low-ability workers, and this sales performance boost is more significant for both low-sales- and low-speed-ability workers than for those high-ability workers. These findings support H3a.

Similarly, the meal duration models (Columns 2 and 4) also seem to suggest that the new technology may reduce meal duration for both high- and low-ability waiters, and this reduction is more substantial for low-ability workers in terms of both sales and speed abilities than for those high-ability ones, supporting H3b. In particular, the coefficients of *System* are significant and negative (-0.1281 and -0.1388), while the coefficients of the interaction terms are significant and positive (0.0593 and 0.0769). Interpreting these coefficients (summarized in 8), we estimate that tabletop technology may reduce meal duration for low-sales-ability waiters by 12.81%, a value that is 5.93% higher than the value increased for high-sales-ability waiters (6.88%). We estimate that tabletop technology reduces meal duration and for the low-speed-ability waiters by 13.88%, a value that is 7.69% higher than the value increased for high-speed-ability waiters (6.19%). In terms of the absolute effects based on the mean meal duration before the implementation, tabletop devices may reduce the meal duration for low-sales-ability waiters by $(12.81\% \times 57.4 \approx 7.35)$ minutes, 3.69 minutes more than for high-sales-ability waiters $(6.88\% \times 53.27 \approx 3.66$ minutes), and for low-speed-ability waiters by $(13.88\% \times 60.92 \approx 8.46)$ minutes, 5.33 minutes more than for high-speed-ability waiters $(6.19\% \times 50.52 \approx 3.13$ minutes). The differences (3.69 minutes and 5.33 minutes) between the high- and low-ability waiters are statistically significant.

In sum, the moderating effects model results seem to suggest that the new technology serves as a "great equalizer" – it does not necessarily make a restaurant's best workers even better; rather, it reduces performance gaps among workers.

Table 7: Moderating Effects by Waiters' Skill Types

	(1) log(*Sales*)	(2) log (*MealDuration*)	(3) log(*Sales*)	(4) log (*MealDuration*)
System	0.0347***	-0.1281***	0.0401***	-0.1388***
	(0.0024)	(0.0070)	(0.0025)	(0.0060)
HighSalesSkill=1	0.0628***	-0.0888***		
	(0.0012)	(0.0044)		
System×HighSalesSkill=1	-0.0131***	0.0593***		
	(0.0012)	(0.0045)		
HighSpeedSkill=1			0.0412***	-0.1718***
			(0.0014)	(0.0034)
System×HighSpeedSkill=1			-0.0198***	0.0769***
			(0.0021)	(0.0034)
PartySize	0.3173***	-0.0073***	0.3175***	-0.0062***
	(0.0017)	(0.0008)	(0.0018)	(0.0007)
log(*MealDuration*)	0.1987***		0.2020***	
	(0.0029)		(0.0031)	
log(*Sales*)		0.1918***		0.1873***
		(0.0023)		(0.0022)
Controls	Yes	Yes	Yes	Yes
H3 Supported	Yes	Yes	Yes	Yes
Observations	2,609,692	2,609,692	2,609,692	2,609,692
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

Table 8: Interpreting the Moderating Effects

	Low Sales Ability	High Sales Ability	Low Speed Ability	High Speed Ability
Sales	3.47% ($1.03)	2.16% ($0.69)	4.01% ($1.24)	2.03% ($0.62)
Meal Duration	12.81% (7.35 minutes)	6.88% (3.66 minutes)	13.88% (8.46 minutes)	6.19% (3.13 minutes)

1. The absolute effects are shown in the parentheses. 2. All the differences between the high and low ability waiters are statistically significant.

4.5 Post-hoc Analysis

4.5.1 Sales Action Impact

Regardless of ability level, waiters can increase their sales performance either through upselling or cross-selling (Tan and Netessine, 2014b,a). Understanding the break-down of the sales items can further help a company update its tabletop systems and train waiters to sell the higher-profit-margin items more effectively.

To answer these questions, we estimate the following models:

$$\log(ItemNum_{ic}) = \alpha_0 + \alpha_1 System_i + \alpha_2 \log(MealDuration_i) + \alpha_3 PartySize_i + \alpha_5 Controls_i + \varepsilon_i \quad \forall c \tag{8}$$

$$\begin{aligned}\log(Sales_{ic}) = \beta_0 + \beta_1 System_i + \beta_2 \log(MealDuration_i) + \beta_3 PartySize_i + \beta_4 ItemNum_{ic} \\ + \beta_5 Controls_i + \xi_i \quad c = FBA,\end{aligned} \tag{9}$$

where $ItemNum_{ic}$ is the number of items sold in category c in check i. We create five categories, which include 1) food (F), 2) non-alcoholic beverages (B), 3) alcoholic drinks (A), 4) the sum of the first three categories (i.e., FBA), and 5) the sum of all items (including a tabletop flat-rate game option). Model 8 is estimated with the five categories separately in five equations to delineate the category-level break-down of the cross-selling effects (i.e., selling more items). In Model 9, we focus on the category of FBA because waiters could not sell the game option before the installation of the tabletop technology. The additional variation in the sales in this category conditioned on the number of sold should then be attributed to upselling action (i.e., selling more expensive items).

Table 9 shows the results of cross-selling and upselling actions. Interpreting the coefficients of *System* in Columns 1 through 5, the new tabletop technology may increase the total number of items sold by 0.3, the number of food-, beverage- and alcohol-related items by 0.1 (2% increase from the average number of sold per check during period I), the number of food items by 0.0582 (1.76% increase), and the number of alcoholic drink items by 0.0581 (13.83% increase), while it may reduce the number of non-alcoholic beverages by 0.0136 (1% decrease). These results suggest that the digital presentation of all menu items on the tabletop system may develop consumers' appetite to order more menu items. In addition, the ease of reordering alcoholic drinks on the tabletop device may boost the alcohol sales so significantly that it may supersede a certain amount of original demand for non-alcoholic beverages. Furthermore, the relatively small increase in the food items sold and the drop in the beverage items sold suggests that restaurants should update their systems to allow ordering food and beverage items directly from the table. Finally, in Column 6, the coefficient of *System* is 0.0204, which implies that tabletop technology may increase sales through upselling by 2%. For example, as evidenced in the sales break-down, some consumers may be upsold to switch from non-alcoholic beverages to more expensive alcoholic drinks. The tabletop system may also free up some waiters' capacity (e.g., settling the checks), thus allowing the waiters to have more time and energy to focus on up-selling activities. The 2% sales increase through upselling constitutes 65% of the total sales lift in the FBA category because the coefficient of *System* in Model 9, excluding the control *ItemNum* is 0.031. The stronger contribution from the upselling compared to cross-selling further suggests more potential cross-selling opportunities if direct tabletop ordering of more of the menu items is allowed or enabled.

Table 9: Sales and Meal Duration Effects Explained by Upselling and Cross-selling Actions

	(1) ItemNum c = All	(2) ItemNum c = FBA	(3) ItemNum c = F	(4) ItemNum c = B	(5) ItemNum c = A	(6) log(*Sales*) c = FBA
System	0.3025***	0.1027***	0.0582***	-0.0136*	0.0581***	0.0204***
	(0.0167)	(0.0165)	(0.0093)	(0.0060)	(0.0068)	(0.0015)
log(*MealDuration*)	1.0530***	1.1048***	0.5965***	-0.0624***	0.5708***	0.0855***
	(0.0175)	(0.0181)	(0.0097)	(0.0043)	(0.0133)	(0.0025)
PartySize	1.6060***	1.5663***	1.0740***	0.4524***	0.0399***	0.1152***
	(0.0068)	(0.0066)	(0.0036)	(0.0027)	(0.0024)	(0.0012)
ItemNum c=FBA						0.1099***
						(0.0007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,609,692	2,609,692	2,609,692	2,609,692	2,609,692	2,609,692
Prob>Chi-sq	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

4.5.2 Restaurant-Oriented Impact

One might suspect that the new technology may affect restaurants' staffing decisions, which can simultaneously influence sales and meal duration (Mani et al., 2011; Tan and Netessine, 2014b,a; Chuang et al., 2016) Hence, it can become unclear whether technology or staffing decisions are driving the main results. We explicitly test the management-related performance indicator of staffing levels. In particular, we first specify an hourly model similar to Models 4 and 5 to examine the average effect of the tabletop device on staffing and then another model to analyze the moderating effect of the restaurants' initial staffing level.

That is,

$$HrWaiters_{rh} = \alpha_0 + \alpha_1 System_{rh} + \alpha_2 \log(HRTables_{rh}) + \alpha_3 Controls_{rh} + \varepsilon_{rh}$$
$$HrWaiters_{rh} = \beta_0 + \beta_1 System_{rh} + \beta_2 System_{rh} \times HighStaffing_r + \beta_3 \log(HRTables_{rh}) + \beta_4 Controls_{rh} + \xi_{rh} \quad , \quad (10)$$

where $HrWaiters_{rh}$ is the number of waiters working during hour t at restaurant r. For the moderating effect, we follow Lu et al. (2017), who study how the effect of a computerized provider order entry system (CPOE) on nursing home staffing decisions depends on the vertical position of the nursing home, and define $HighStaffing_r$ as a binary variable, with one if the hourly average staffing level is above the sample median during period I (median = 5), when no restaurants implemented the tabletop technology, and zero otherwise. In addition to the temporal and locational fixed effects controls (i.e., $Controls_{rh}$), we adjust for the number of checks opened in an hour because restaurants use this factor to forecast traffic and determine staffing levels. Note that we do not utilize the individual *HighStaffing* term in Model 10 because it is time invariant and absorbed into the restaurants' fixed effects in $Controls_{rh}$.

Table 10 shows the results of restaurant-oriented impact. Similar to the results reported in Lu et al. (2017), the coefficient of *System* turns out to be statistically insignificant in the main effect model, which suggests that the implementation of the tabletop technology did not seem to change the staffing levels on average. In other words, the substitution effect of technology may cancel out the complementarity effect on average. After talking with the corporate office, we further realized that managers may have been concerned that the waiters would perceive the new technology as a threat to replace part of their jobs, which could negatively impact employee morale. Therefore, the restaurants in our sample seemed to choose to stay with their regular staffing decisions on average. However, across the restaurants, we observe heterogeneous effects of tabletop technology on staffing decisions, depending on pre-installation staffing levels. The coefficient of *System* is significant and positive (0.0895), which suggests that the new technology may have increased the hourly staffing levels of those restaurants staffed below the median during period I by 0.0895 person per hour, which is approximately $(0.0895/4.28 \approx 2\%)$ of the sample mean or approximately one additional waiter every 50 hours for each store. By contrast, the coefficient of the interactive term is significant and negative (-0.1749), implying that the tabletop technology may have reduced the staffing levels of those restaurants that initially had high staffing levels during period by $(0.1749 - 0.0895 = 0.0854)$ person per hour, down by approximately $(0.0854/5.61 \approx 1.5\%)$ from the sample mean. The restaurants that initially had low staffing levels may have chosen to increase staffing after adopting the tabletop technology in order to gain the competitive advantage of increased labor productivity because of the new technology (i.e., complementarity effect of technology). However, restaurants that had high initial staffing levels may have decided to lower staffing to control cost because the concavely increasing labor output may be outweighed by constant marginal staffing costs (i.e., substitution effect of technology) (Lu et al., 2017). Despite the heterogeneous effect directions, the size of the effects are relatively small compared to the results in Lu et al. (2017), suggesting that the additional staffing is approximately 7.6% from the mean, and that the staffing reduction is approximately 5.8% from the mean. To summarize, the unchanged average staffing levels and the relatively small heterogeneous effect sizes rule out an alternative explanation of our main results and render our quasi-experimental setting of the technology implementation "pure".

Table 10: Restaurant-Oriented Impact

	HrWaiters	*HrWaiters*
System	0.0261	0.0895*
	(0.0378)	(0.0426)
System×HighStaffing		-0.1749**
		(0.0611)
log(*HrTables*)	1.9883***	1.9881***
	(0.0342)	(0.0342)
Controls	Yes	Yes
Observations	215,532	215,532
Prob>Chi-sq	<0.001	<0.001

1. Standard errors are shown in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

4.6 Managerial Implications

The empirical results of the impact of new tabletop technology afford insights into long-term effects, such as changes in business processes, organization structure and innovation in customer and supplier relations (Brynjolfsson and Hitt, 2003).

First, our results suggest that tabletop technology may increase average sales per check by close to 3%. This sales lift (i.e., the value of the tabletop technology) may translate to \$6 million per month for a restaurant chain that generates approximately \$200 million in revenues per month. Currently, according to reports from our focal chain, the company pays the tabletop device-maker a subscription fee and receives a portion of the 99 cent flat fee from customers who play games. One in every 10 customers of the 20 million customers visiting each month pays to play the games. Assuming an average party size per check of approximately two people, as in our data, we estimate that the profitability of the technology should be $6 - (20/2) \times 0.1 = \$5$ million per month. This additional profitability is substantial for casual dining companies because of their traditionally low profit margins and ever increasing competition within the sector and from the growing fast-casual dining sector. Admittedly, strong competition from late adopters of tabletop technology may lower the return of the current technology for our focal restaurant in the long run. However, the company's digital innovation initiative to improve its business process (e.g., the company may consider menu recommendation or allows customers to order more food from the tabletop device) and its experience accumulated from analytics should enable the company to continue gaining considerable advantage over its competitors.

Second, the company has left its staffing levels relatively unchanged after implementing the tabletop technology. In other words, the company seems to incur additional cost to maintain close waiter-customer relationships. It is true that waiter-customer interaction is an integral part in casual dining service. Waiters do not simply bring the food to the table, but they also need to make customers feel welcomed, comfortable, and look forward to their dining experience (Meyer, 2008). Nevertheless, we recommend that the restaurant should consider experimenting with staffing levels to fully reap the benefits of the tabletop technology because reducing staffing levels may not necessarily compromise service quality. According to Tan and

Netessine (2014b), increasing workload (in terms of the number of tables that a waiter simultaneously handles) to an optimal level may put casual dining waiters "in the zone" to feel motivated to expend more effort in sales (too many tables, of course, may overload waiters and reduce their performance). Indeed, reducing staffing levels may not only increase sales, but also reduce labor costs, adjusting for everything else. Replicating the econometric approach of Tan and Netessine (2014b) in our focal restaurants, we find that the optimal workload is about 0.8 tables/waiter above the current sample mean (2.77 tables/waiter) and that the optimal staffing level is 3.42 waiters per hour (a 23% reduction). Our findings suggest that 77% of the time, restaurants in our study may be overstaffed by 1.42 waiters. If the restaurants can reduce their staffing levels to achieve the optimal workload (3.56 tables/waiter) every hour, they may achieve a 3% sales lift, separate from the tabletop technology's ability to increase workers' capacity in serving their customers. We need to caution that the actual sales lift may be smaller than 3% in practice because sales forecasts may be inaccurate and managers may face various constraints in ensuring optimal staffing levels, such as minimum shift length requirements (Mani et al., 2011). Furthermore, managers may consider cross-training extra waiters to learn kitchen responsibilities in order to meet the increased demand created by the tabletop technology. In sum, our analysis suggests that restructuring labor staffing decisions has the potential to simultaneously increase revenues and save labor costs, which is particularly valuable in service industries, like casual dining, which incur significant labor costs.

Third, our results reveal that the customers who pay with the tabletop technology and actively engage with the device are associated with both higher spending and shorter meal duration. In other words, these tech-savvy customers are both valuable and efficient. Xue et al. (2011) find that these customers are young, highly educated, and they have considerable loyalty with the company. The restaurant chain should strategically advertise to attract more such customers and win their loyalty and repeated visits. For example, we applaud the focal restaurant chain for recently starting a loyalty program that allows customers to log into the tabletop technology to win points from their purchases and redeem points and other coupons sent via email. The restaurant chain also may consider marketing its digital innovation at technology-related online forums and media outlets. The company also should enhance its engagement with customers via social media and mobile app platforms.

5 Conclusion

In this study, we analyze granular POS data from 66 casual full-service restaurants and employ a difference-in-difference technique to identify the causal impact of a new tabletop technology on restaurant performance. We find that the tabletop system may increase the average sales per check by close to 3% and reduce the meal duration by approximately 10%. Various robustness checks, including showing the parallel pre-installation trends of the treated and the control restaurants, and the insignificant correlation between the pre-installation restaurant characteristics and installation timing decisions, provide assurance of the validity of our empirical technique. In addition, the results are not due to a Hawthorne effect because the results hold for up to eight weeks after the installation of the tabletop system. Furthermore, we show that those customers who pay their checks with the tabletop instead of with a waiter are associated with higher spending and shorter meal duration, aligning with previous theories on customer efficiency. In addition, customer engagement level with the tabletop technology has a J-shaped relationship with spending and a reversed-J-shaped relationship with meal duration. For the waiters, we discover that new technology helps reduce the performance gaps between high-ability waiters and low-ability waiters in that the tabletop technology increases sales and reduces meal duration at higher levels for low-ability waiters than for high-ability ones. In addition, the new technology helps waiters conduct more effective upselling and cross-selling. For restaurant management, the expectation that new technology will reduce labor costs was unsupported; instead, we find that traffic and staffing levels were stable with the installation of tabletop technology. The unchanged traffic and staffing levels, nevertheless, provided us with a "cleaner" setting to delineate the singular impact of technology on the sales and meal duration per check.

Our findings allow us to calculate the value of the tabletop technology in our empirical setting. We estimate that the 3% sales lift per check may translate into $6 million extra sales or $5 million in profit per month in the short run, which is practically significant for an industry characterized by a low profit margin. It is worth noting that the tabletop deployment in our setting is an example of a "soft" technology introduction, in that it did not radically change the existing business model, thus making our impact estimates conservative. Equally important, the data collected in the tabletop devices and the company's digital innovation initiative to improve its business process (e.g., the company may consider menu recommendation or allows customers to order more food from the tabletop device) should enable the company to continue increasing value and gaining considerable advantage over its competitors in the long run. Furthermore, our results suggest that restaurant management should re-evaluate its labor decisions to fully reap the benefits of tabletop technology because reducing the staffing levels of waiters may not necessarily compromise service quality. Remaining waiters may be motivated to work harder, and extra waiters may be retrained to add new capacity-constrained roles. Finally, restaurants should strategically and creatively advertise to attract more technology-savvy customers and win their loyalty because these customers tend to be more valuable and efficient.

Our paper also makes several contributions to the academic literature. First, our research adds to a growing stream of literature of using granular-level observational data to understand the impact of tabletop technology on firm and labor productivity in an applied setting. Second, we provide empirical evidence regarding a customer-facing technology, which is attracting increased interest in the restaurant industry, an industry that has recently begun to embrace in technology innovation. Third, we examine customer-oriented, worker-oriented and restaurant-oriented effects of tabletop technology in a people-intensive service industry with close worker/consumer interaction, which contributes to the analytical framework for value co-production in services (Roels, 2014; Karmarkar and Roels, 2015).

Our research has certain limitations, which create exciting opportunities for future researchers to overcome. First, due to data limitation, we were only able to study the effect of tabletop technology on restaurant performance within the first year after system implementation. In other words, our research is restricted to being a short-term-effect study, even though we recognize the value of studying a longer-term effect (Campbell and Frei, 2010). Second, our data cannot identify unique customers, and thus it lacks the ability to study other important questions such as customer retention rates and customer population dynamics. As the restaurant chain has just introduced a customer loyalty program, which asks customers to identify themselves on the tabletop device to earn and redeem points, the new data should afford excellent opportunities to analyze how to manage the company's relationships with individual customers. Finally, although we examine the coded data about customers' engagement level with the tabletop device, we do not observe the actual browsing history on the device. By combining browsing history and real-time inventory data, future researchers can use analytics to recommend menu items or provide real-time promotion to targeted customers.

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