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, other 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 approximately 1% (95% confidence interval is from 0.8% to 1.02%), and reduce the meal duration by close to 10% (95% confidence interval ranges from -9.94% to -9.54%). The combination of these two effects increases the sales per minute or sales productivity by approximately 11%. Various robustness checks of our empirical strategy and post-hoc analyses find that tabletop technology allows low-ability waiters to improve their performance more significantly than high-ability waiters. In addition, the technology does not change the staffing level. 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

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1 Introduction

Information technology has been found to be associated with higher productivity by reducing costs, increasing output quality, and providing intangible benefits 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. 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 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. Naturally, 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 waiters and restaurant management, respectively. We find that tabletop technology is likely to improve average sales per check by approximately 1% and reduce meal duration by approximately 10%, increasing the sales per minute or sales productivity by approximately 11%. 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. It is not because low-ability waiters, who have a stronger need for the technological assistance, actually use the technology more frequently than the high-ability waiters. Rather, the technology duplicates what the high-ability waiters already deliver. The new technology also helps waiters more effectively upsell and cross-sell. We find no significant changes in staffing levels or store traffic due to the technology.

Our research findings highlight the value of technology innovation for restaurant operations. We also generate insights for managers to consider changes in staffing decisions and the functions of the new systems to fully exploit the productivity gains from the new technology.

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 the 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. Campbell and Frei (2010) find that use of an online banking channel substitutes the usage of ATMs and voice response units, augments service consumption at branch and call centers, and increases 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 additionally examines 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, an industry that offers significant opportunity for growth in technology innovation. Third, we examine 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, re-order beverages and alcoholic items, 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 Predictions

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.*

The impact of new technology also depends on another variable – that of the service provider's (i.e., waiter's) skill level. 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 ability (as explained in Hypothesis 1). However, waiters have varying innate skill levels in these two types of skill dimensions (Tan and Staats, 2017), so some may benefit from technology more than others. We anticipate that the technology is likely to help either low-sales-ability or low-speed-ability waiters improve their sales and meal duration aspects of performance more significantly than their high-ability counterparts for two potential reasons.

First, the gained sales or speed performance improvement from technology is more likely to duplicate what high-sales-ability or high-speed-ability waiters 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, either sales or meal duration performance improvement may approach an asymptotic limit as the waiter's sales or speed ability increases. High-sales-ability or high-speed-ability waiters may already offer the higher sales-generating superior service quality that the tabletop technology aims to complement. For example, similar to the tabletop's colorful pictures and well-written textual descriptions, 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-sales-ability or high-speed-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. In short, tabletop devices aim to deliver the types of high performance services that high-sales-ability or high-speed-ability waiters may already offer.

Second, low-sales-ability or low-speed-ability waiters have a stronger need and may be more inclined to turn to tabletop technology for help than their high-ability counterparts 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-sales-ability or low-speed-ability waiters may perceive greater benefits from tabletop technology than high-ability waiters 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-speed-ability waiters may more enthusiastically introduce the device's function to settle the check at the table to the customers than their high-speed-ability coworkers may, to quicken the check settlement process. Similarly, low-sales-ability waiters may actively encourage the customers to read the menu descriptions on the device because they may not be as knowledgeable about the menu as the high-sales-ability waiters. Encouraging the use of the tabletop technology should further maximize its performance boost.

For these two reasons, we posit that

HYPOTHESIS 2a: *The tabletop technology increases the sales for either low-sales-ability or low-speed-ability waiters more significantly than for high-sales-ability or high-speed-ability ones, everything else being equal.*

HYPOTHESIS 2b: *The tabletop technology increases service speed for either low-sales-ability or low-speed-ability waiters more significantly than for high-sales-ability or high-speed-ability ones, everything else being equal.*

3 Empirical Strategy

3.1 Data

We collected the data directly from the restaurant chain on 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. Table 1 shows the installation months 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 had 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 all the restaurants had 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

[1]As a robustness check, we focus 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 exclude the handful restaurants that implemented the devices before December 2013 from our sample (13 in total). Finally, we analyze all the observations during period II. The results are shown in the Appendix, which support our main results both qualitatively and quantitatively. Focusing on one continuous period provides a classic difference-in-difference setting

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).

Table 1: Tabletop Installation Months

Installation Date	Number of Restaurants Involved
3/31/2013	1
4/30/2013	4
9/30/2013	3
11/30/2013	5
12/31/2013	2
1/31/2014	7
2/28/2014	2
3/31/2014	42

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 orders counter serves as a placebo test, on which we will elaborate in Subsection 4.2.3. Furthermore, we eliminate the day's top 5% and bottom 5% of checks in terms of check sizes 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. As robustness checks, we analyze both the full data set and a data set that sequentially drops the observations that are four standard deviations away from the sample check size average and party size average[2], and we find consistent results (see Appendix).

Table 2 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

and corroborates our main results.

[2]We thank an anonymous reviewer for this advice.

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 sales 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. The hourly number of waiters staffed seems to remain constant over time, with the average being 4.76 during period I, 4.37 during period II and 4.45 during period III.

Table 2: Summary Statistics of Check-level Observations

		Period 1 (12/2012 - 2/2013)		Period II (12/2013 - 2/2014)		Period III (5/2014 - 7/2014)	
	Definition	Mean	SD	Mean	SD	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
ItemQuantity	Number of items sold	5.02	2.65	5.08	2.69	5.30	2.84
FoodQuantity	Number of food items sold	3.33	1.77	3.35	1.77	3.43	1.85
BeverageQuantity	Number of beverage items sold	1.29	1.14	1.27	1.13	1.26	1.13
AlcoholQuantity	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
HrWaiters	Hourly number of waiters	4.76	2.36	4.37	2.19	4.45	2.21
HrTables	Hourly number of checks opened	12.66	8.06	12.10	7.72	11.59	6.98
Observations		896,825		851,081		862,624	

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 3). As expected, *Sales* is positively correlated with *MealDuration* (0.2529), the variables representing the number of items sold (i.e., *ItemQuantity* (0.9088), *FoodQuan-*

tity (0.8238), *BeverageQuantity* (0.4625), *AlcoholQuantity* (0.3537)), and *PartySize* (0.7434). *MealDuration* is also positively correlated with those variables related to the number of items sold (0.2207, 0.2044, 0.0296, 0.1698, respectively) and *PartySize* (0.1420). Among the breakdown of the types of the items sold, *FoodQuantity* positively correlates with *BeverageQuantity* (0.4128) and *AlcoholQuantity* (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 *BeverageQuantity* and *AlcoholQuantity* 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 3: Check-level Correlation Matrix

	Sales	*MealDuration*	*ItemQuantity*	*FoodQuantity*	*BeverageQuantity*	*AlcoholQuantity*
Sales	1.0000					
MealDuration	0.2529*	1.0000				
ItemQuantity	0.9088*	0.2207*	1.0000			
FoodQuantity	0.8238*	0.2044*	0.8946*	1.0000		
BeverageQuantity	0.4625*	0.0296*	0.6152*	0.4128*	1.0000	
AlcoholQuantity	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) estimation 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:

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

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

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

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 per check 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; 3) sales per minute reflects sales productivity, and 4) micro-level data typically reveal more information than aggregate-level data. We consider a break-down of the number of items sold in terms of food, beverages, and alcoholic drink items in Section 4.3 as additional analysis to show the insights about the tabletop technology impact. We also consider hourly total sales as an alternative performance measure and a robustness check in Subsection 4.2.4.

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 assesses the impact of the system on the restaurant performance. The tabletop technology potentially affects both sales and meal duration, which are typically positively associated with each other. In other words, the technology can directly affect sales (meal duration) and indirectly affect sales (meal duration) via meal duration (sales). In order to delineate the pathway of the impact of the technology, we control for the meal duration in the sales model (Model 1), and vice versa (Model 2), capturing the *direct* effects of the technology on sales and meal duration. We also estimate two models excluding sales and meal duration controls to estimate the *total* effects of the technology. For these two total effects models, we adopt a seemingly unrelated regression approach to adjust for the correlation between sales and meal duration.

In all the 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 weeks, 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 the tabletop technology, and they have been used extensively in the literature that references restaurant data. We then cluster the standard errors at both store and day level to allow for correlation within store and heteroskedastic errors over time. The clustered robust errors can correct for overconfidence of the estimates because check-level sales and meal duration are likely to be correlated within the store and the day.

4 Results

4.1 Treatment Effects

Table 4 shows the treatment effects of tabletop technology on the restaurant performance. The coefficient of *System* in the sales model is significant and equal to 0.0102 in Column 1, suggesting that the total effect of the tabletop technology on sales per check is approximately 1% ($0.3 out of the average check size of $30.45 during period I). Its 95% confidence interval ranges from 0.8% to 1.2%. The coefficient of *System* in Column 3 is significant and equal to 0.0288, which suggests the direct effect conditioned on the meal duration is estimated to be approximately 2.9% (or $0.88). It has a 95% confidence interval between 2.4% and 3.3%. The indirect effect is approximately equal to $-0.0994 \times 0.1917 \approx -1.9\%$, which is the multiplication between the coefficient of *System* in Column 4 and the coefficient of log(*MealDuration*) in Column 3. Its 95% confidence interval ranges from -2.1% to -1.7%. The indirect effect is negative because the technology reduces the meal duration, which is positively associated with sales. No sales can be generated when the meal is concluded. Either the 1% total effect or the 2.9% direct effect on sales is practically significant, given the low-margin nature of the casual dining industry.

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). Its 95% confidence interval ranges from -9.94% to -9.54%. It primarily consists of a direct effect conditioned on sales, -9.94% (95% confidence interval is from -11.1% to -8.8%), shown in the *System* coefficient in Column 4 and a minimal indirect effect via sales. The indirect effect is estimated to be 0.0288 (the coefficient of *System* in Column 3) $\times 0.1859$ (the coefficient of log(*Sales*) in Column 4) $\approx 0.5\%$. Its 95% confidence interval falls between 0.5% and 0.6%. The indirect effect is positive because a larger check typically takes longer. Note that the 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 Column 4. With increased sales and shorter meal duration per check, Column 5 shows that tabletop technology is estimated to increase sales productivity by 10.77% ($0.06/minute out of the average sales productivity of $0.55/minute during period I).

Furthermore, the coefficients of the control variables demonstrate associations in expected directions. For example, the coefficient of log(*MealDuration*) is 0.1917 in the sales model, while the coefficient of log(*Sales*) is equal to 0.1859 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 (0.3286 and 0.318), matching expectation. *PartySize* is positively associated with meal duration in Column 2 (0.0553), but it becomes negative in Column 4 (-0.0058) with the sales control. The sign flips because Column 4 measures how long it takes to finish a meal, normalized by its dollar value. In other words, the more people in the party, the faster the party is typically going to finish a fixed size meal.

Table 4: Check-level Impact of Tabletop Technology on Restaurant Performance

	(1) log(*Sales*)	(2) log(*MealDuration*)	(3) log(*Sales*)	(4) log(*MealDuration*)	(5) log(Sales/MealDuration)
System	0.0102***	-0.0974***	0.0288***	-0.0994***	0.1077***
	(0.0010)	(0.0010)	(0.0023)	(0.0058)	(0.0060)
PartySize	0.3286***	0.0553***	0.3180***	-0.0058***	0.2735***
	(0.0002)	(0.0002)	(0.0020)	(0.0009)	(0.0021)
log(*Sales*)				0.1859***	
				(0.0026)	
log(*MealDuration*)			0.1917***		
			(0.0034)		
Controls	Yes	Yes	Yes	Yes	Yes
H1 Supported	Yes	Yes	Yes	Yes	Yes
Observations	2,609,692		2,609,692	2,609,692	2,609,692
Adjusted R-squared	0.531 (jointly estimated by SUR)		0.546	0.124	0.331

1. Standard errors are shown in parentheses. In particular, clustered standard errors at store and day level are provided in Columns 3 through 5.

2. *p≤ .05, **p≤ .01, ***p≤ .001.

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 should have followed similar performance trends without the system 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 suggests limited heterogeneity and 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 uniform management style.

Second, the restaurants are all located in the same metropolitan area, thus making geolocational and macroeconomic trends comparable across the locations.

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. Our data captures 11 restaurants that implemented the technology during period II, which includes two in December 2013, seven in January 2014, and two in February 2014. For illustration purposes, we focus on the seven restaurants (defined as the treatment group) that installed the tabletop systems during the same week in January (108th week in our sample), and 44 restaurants did not yet have the systems installed (defined as the control group). We exclude the 15 restaurants that implemented the systems before January, 2014.

Figures 1a and 1b show the weekly average sales and meal duration per check of both the treated and the control groups before and after the 108th week when seven restaurants installed the tabletop technology (represented by a vertical line). The treated and the control restaurants seem to have similar linearly-fitted trends before the installation week. Note that, although the control group persistently shows a longer meal duration than the treatment group (i.e., higher level), their different meal duration levels will be removed by the DID estimation. Equally important, we estimate weekly pre-installation growth rates of sales and meal duration, respectively. The results are presented in Table 5. While the *WeekTrend* (i.e., a linear continuous variable of weeks with an increment of one unit for each consecutive week) is significant in the sales model for the control restaurants, the differences of the *WeekTrend* coefficients turn out to be statistically insignificant (p-values are 0.6959 and 0.6914) in both sales and meal duration models. In sum, both the visual checks and the indifferentiable growth rates suggest that the parallel trends assumption should be valid before the technology installation for this sample. We further repeat the visual checks and estimation of the pre-installation growth rates for another two installation months during period II (i.e., two restaurants in December, 2013, and two in February, 2014). The results are provided in the Appendix, and they robustly support the parallel trends assumption.

In order to address potential endogenous selection bias of restaurants to implement the technology be-

Figure 1: 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

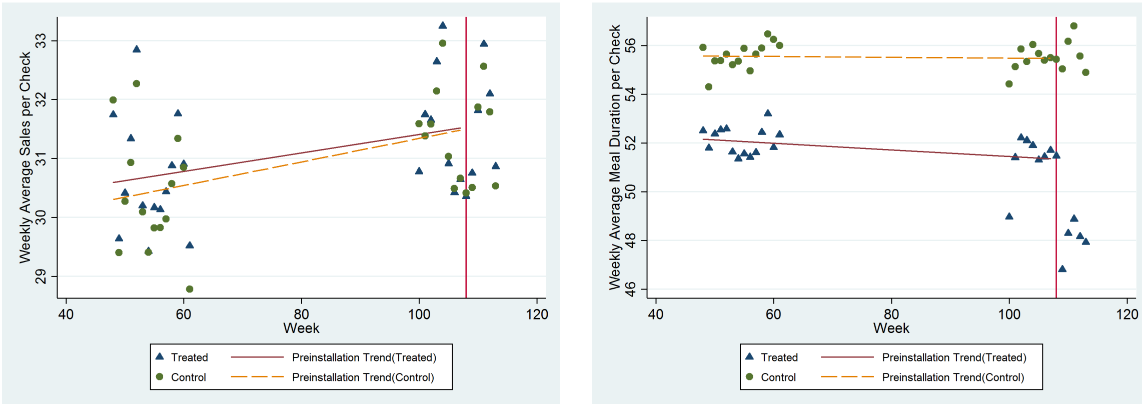


Table 5: Pre-installation Weekly Growth Rates during Periods I and II

	log(*Sales*)	log(*Sales*)	log(*MealDuration*)	log(*MealDuration*)
	Treated	Control	Treated	Control
WeekTrend	0.0004	0.0006*	-0.0000	0.0001
	(0.0003)	(0.0002)	(0.0001)	(0.0001)
PartySize	0.3281***	0.3294***	0.0557***	0.0532***
	(0.0018)	(0.0014)	(0.0009)	(0.0005)
Controls	Yes	Yes	Yes	Yes
Observations	148,187	916,314	148,187	916,314
Adjusted R-squared	0.509	0.517	0.066	0.083

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

fore the mass roll-out, we first estimate a logit model and a probit model to examine what type of restaurants were selected to implement the technology during January, 2014. We then match all the treated restaurants with those that had not implemented the technology, and we repeat analysis on this smaller but more homogeneous matched sample.[3] In the logit/probit models, we specifically include four predictors: *PreAvgSales*, *PreAvgMealDuration*, *PreAvgTables,* and *PreAvgStaffing,* which measure the average check size, the average meal duration, the average hourly number of tables/parties seated and the average hourly number of waiters staffed before the system implementation, respectively. We a priori postulate that restaurants may consider these factors when choosing where to implement the tabletop system first because the system is related to improving sales and efficiency performance.

[3]We thank the AE for this valuable suggestion.

Columns 1 and 2 in Table 6 show the results. As can be seen, all the coefficients are statistically insignificant except *PreAvgMealDuration* in the probit model, with a negative coefficient (-0.1684). These results suggest that the treatment restaurants are generally comparable with the control restaurants, which supports the exogenous installation timing assumption. Nevertheless, those restaurants that tended to have shorter meal duration may have been more likely to implement the technology in January 2014 than those that had longer meal duration, which is consistent with our visual check in Figure 1b.

Although we cannot completely rule out the endogeneity (e.g., the chain chose restaurants with shorter meal duration to install the technology in January 2014), we do not believe this possibility significantly drives our results for the following reasons. First, despite shorter meal duration, the treated restaurants have similar trends with the control restaurants. Thus, the DID methodology can still identify the treatment effect because the difference in the pre-treatment levels will be differenced out by the difference in the post-treatment levels.

Second, the result suggesting that the chain targeted those restaurants having shorter meal duration to implement the technology in January 2014, actually makes our estimated effect of technology on meal duration conservative. A restaurant having short meal duration may have already been efficient enough, making it difficult and costly for the tabletop technology to reduce meal duration further (i.e., the floor effect). Admittedly, one could argue that customers going to the early-adopting restaurants may be more time-sensitive than those going to the late-adopting ones, which would provide an alternative explanation to the technological effects. We find the customers in the early adopting restaurants do not necessarily use the tabletop technology more frequently than those in the late-adopting ones. Only 55% of the checks were paid with the tabletop systems in the early-adopting restaurants, while 62% of the checks that were paid with the tabletop systems in the late-adopting restaurants. In addition, the early adopting restaurant customers do not necessarily order more items per unit of time than the late adopting restaurant customers. The average numbers of items ordered normalized by meal duration are 0.0966 items/minute, and 0.1041 items/minute in the early- and late-adopting restaurants, respectively. In sum, these two pieces of evidence suggest that the restaurants do not necessarily target those early adopting restaurants because their customers are more time-sensitive.

Third, we apply matching on the data to reduce heterogeneity and we find consistent results. In particular, we use *PreAvgSales, PreAvgMealDuration, PreAvgTables* and *PreAvgStaffing* to compute the propensity scores of implementing the technology. We then match each treatment restaurant with comparable control restaurants, using an optimal full matching method (Hansen, 2004). This method minimizes a weighted average of the estimated propensity scores between each treated restaurant and each control restaurant in a subclass. After matching, we check the balance improvement to confirm the matching reduces heterogeneity in the matched subclasses. We then focus on period I and period II and re-estimate our main effect models. Table 17 in the Appendix shows the results, which are congruent with the results reported in Table 4 without matching. We also provide more detailed explanation of our matching procedures in the Appendix.

Table 6: Logit and Probit Models of Receiving Treatment

	(1) January 2014 =1 Estimated by Logit Model Unmatched sample	(2) January 2014 =1 Estimated by Probit Model
PreAvgSales	0.1987	0.1080
	(0.4416)	(0.2450)
PreAvgMealDuration	-0.2903	-0.1684*
	(0.1499)	(0.0830)
PreAvgTables	0.3388	0.1813
	(0.6775)	(0.3582)
PreAvgStaffing	-1.6763	-0.9415
	(2.2002)	(1.1760)
Observations	51	51

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

Ideally, we would like to conduct the visual checks of parallel trends for all the installation dates. However, due to the limitations of our data, we only observe the immediate pre-treatment data for these three months. To alleviate the generalizability concern, we additionally conduct robustness checks of controlling for restaurant-specific trends. In other words, we introduce the interaction between the week categorical variables and the store fixed effects in Models 1 and 2. Table 7 shows the results, which are both qualitatively and quantitatively consistent with the main results in Table 4.

Table 7: Controlling for Restaurant-Specific Week Fixed Effects

	log(*Sales*)	log(*MealDuration*)
System	0.0341***	-0.1269***
	(0.0073)	(0.0072)
log(*Sales*)		0.1861***
		(0.0006)
log(*MealDuration*)	0.1932***	
	(0.0006)	
PartySize	0.3179***	-0.0059***
	(0.0002)	(0.0003)
Controls†	Yes	Yes
Observations	2,609,692	2,609,692
Adjusted R-squared	0.547	0.131

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

†: weekly FEs×*stores* instead of weekly FEs and stores alone.

We finally regress the installation dates (a continuous variable of daily trends with a larger number indicating a later date) on the installation average sales, meal duration per check (i.e., *PreAvgSales*, and *PreAvgMealDuration*), average hourly traffic in terms of the number of parties/tables (*PreAvgTables*) and average hourly staffing levels (*PreAvgStaffing*) in order to determine whether or not there is a systematic bias towards the installation dates in the entire sample. Table 8 shows the results of the regression of installation dates on the pre-installation performance. All the coefficients turn out to be statistically insignificant, suggesting that these factors are all uncorrelated with the implementation date.

4.2.2 Persistent Effects

A potential confounding factor of the true effect of technology implementation on organizational 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 persistent effect of the tabletop technology. In other words, we replace *System*

Table 8: Pre-installation performance and Implementation Dates

	Installation Date
PreAvgSales	11.7044
	(10.8915)
PreAvgMealDuration	-2.9587
	(3.5044)
PreAvgTables	-0.1590
	(0.1889)
PreAvgStaffing	13.9033
	(48.9049)
Observations	66
Adjusted R-squared	0.065

1. Standard errors are shown in parentheses.

2. *p$\leq$ .05, **p$\leq$ .01, ***p$\leq$ .001.

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 illustrated in Figure 2.The circles are the point estimates of the week, while the lines going through the dots indicate their 95% confidence intervals. We observe that both sales and meal duration effects are likely to be persistent because the coefficients are statistically significant and direction is consistent with the main results. 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.

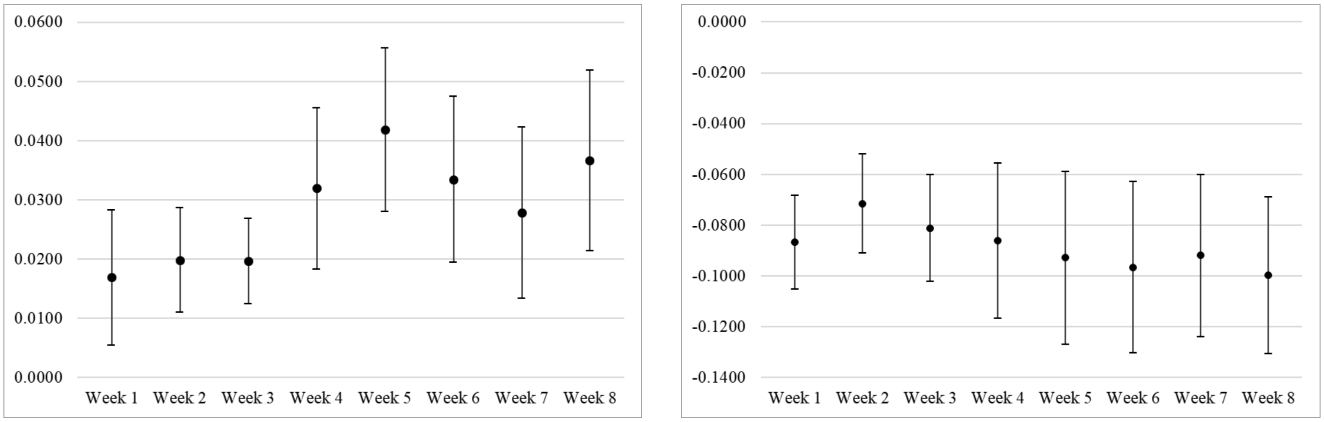
4.2.3 Placebo Tests

In order to alleviate the concern of finding false-positive results in our study (Bertrand et al., 2002), we conduct two types of placebo tests. In the first, we follow the approach suggested in Pierce et al. (2015) and randomly assign the actual implementation dates of the tabletop technology to the 66 restaurants, refitting our Models 1 and 2 60 times. In the second, we collect the POS data from the to-go orders of these restaurants. The to-go orders did not utilize the tabletop technology, so we expect the coefficient of *System* to be insignificant.

Figure 2: Persistent Effects

(a) Eight Weeks Post-Installation Point Estimates of Sales Effects and Their 95% Confidence Intervals

(b) Eight Weeks Post-Installation Point Estimates of Meal Duration Effects and Their 95% Confidence Intervals



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 (the rightmost 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 original estimates capture the main effects of the tabletop technology (the results are presented in the Appendix).

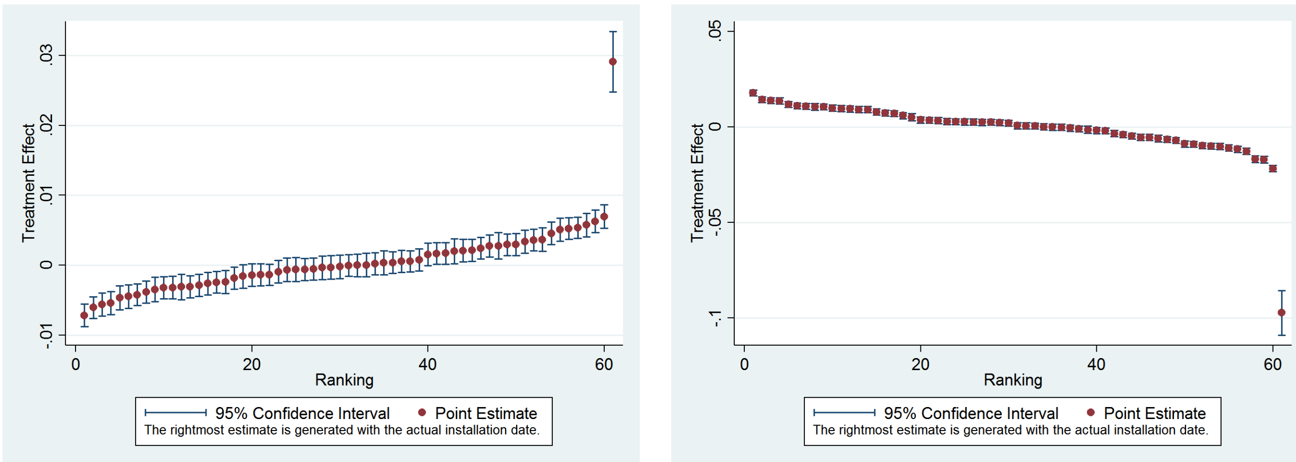
4.2.4 Hour-level Analysis

In addition to the check-level analysis, we conduct 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

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



will be provided in Section 4.4.2). Specifically, we employ the following hour-level models:

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

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

$$\log(HrTotalSales_{rh}) = \gamma_0 + \gamma_0 System_{rh} + \gamma_1 Controls_{rh} + \theta_{rh}$$

where $HrAvgSales_{rh}$, $HrAvgMealDuration_{rh}$ and $HrTotalSales_{rh}$ represent the hourly average sales per check, meal duration per check and total sales 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 weeks, and the stores.

Table 9 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 suggests 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. In fact, the coefficient of *System* in the *HrTotalSales* model is significant and equal to 0.0404, which is comparable with the estimate in the *HrAvgSales* model. Finally, we repeat our analysis at the daily and weekly levels and find qualitatively and quantitatively consistent results (the results are provided in the Appendix).

Table 9: Hour-level Analysis of the Impact of Tabletop Technology on Restaurant Performance

	log(*HrAvgSales*)	log(*HrAvgMealDuration*)	log(*HrTotalSales*)
System	0.0284***	-0.0904***	0.0404***
	(0.0039)	(0.0064)	(0.0076)
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	Yes
Observations	215,527	215,527	215,527
Adjusted R-squared	0.332	0.131	0.077

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

4.3 Waiter-Oriented Impacts

In order to test our H2, 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 $SpeedSkill_j$ for 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). For interpretation purpose, we then negate *SpeedSkill,* so that a higher value of *SpeedSkill* indicates a prompter waiter. A higher value of *SalesSkill* implies a waiter who can generate more sales.

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

$$\log(Sales_i) = \alpha_0 + \alpha_1 System_i(1+\alpha_2 SalesSkillLevel_i) + \alpha_3 SalesSkillLevel_i + \alpha_4 System_i(1+\alpha_5 SpeedSkillLevel_i)+$$
$$\alpha_6 SpeedSkillLevel_i + \alpha_7 \log(MealDuration_i) + \alpha_8 PartySize_i + \alpha_9 Controls_i + \varepsilon_i$$
$$\log(MealDuration_i) = \beta_0 + \beta_1 System_i(1+\beta_2 SalesSkillLevel_i) + \beta_3 SalesSkillLevel_i + \beta_4 System_i(1+\beta_5 SpeedSkillLevel_i)+$$
$$\beta_6 SpeedSkillLevel_i + \beta_7 \log(Sales_i) + \beta_8 PartySize_i + \beta_9 Controls_i + \xi_i.$$

In these models, we define $SalesSkillLevel_i$ and $SpeedSkillLevel_i$ as the sales and speed skill levels of the waiter, associated with check *i.* We separately use two binary definitions and one continuous operationalization of the two variables to ensure the robustness of our variable definitions. In particular, we define *SalesSkillLevel* and *SpeedSkillLevel* as binary variables with either a median or a mean cutoff. They are equal to one if the waiter is above the median (or the mean) of *SalesSkill* and *SpeedSkill*, respectively, and zero otherwise. We alternatively use the continuous *SalesSkill* and *SpeedSkill* to define *SalesSkillLevel* and *SpeedSkillLevel*. In short, under all the definitions, a larger value of either *SalesSkillLevel* or *SpeedSkillLevel* indicates higher ability.

Table 10 shows the results of the moderating effects by waiters' skill levels. Among the findings, in the sales models (Columns 1, 3, 5), the coefficients of *System* are significant and positive, while their interaction terms with both *SalesSkillLevel* and *SpeedSkillLevel* are negative. These results suggest that the tabletop technology is likely to improve sales performance for either low-sales-ability or low-speed-ability waiters even more than for their high-ability counterparts. In addition, in the meal duration models (Columns 2, 4, 6), the coefficients of *System* are significantly negative, while their interaction terms with both *SalesSkillLevel* and *SpeedSkillLevel* are positive. The results imply that tabletop technology may improve the service time for either low-sales-ability or low-speed-ability waiters more than for the high-ability waiters. These findings support both H2a and H2b.

Table 11 presents the interpretation of the moderating effects of the binary skill types in terms of the median cutoff. Tabletop technology may improve the sales performance for low-sales-ability, low-speed-ability waiters by 3.63%, a value that is 0.69% higher than for high-sales-ability, low-speed-ability waiters (2.94%), 1.13% higher than for low-sales-ability, high-speed-ability waiters (2.5%), and 1.82% higher than for high-sales-ability, high-speed-ability waiters (1.81%). Similarly, tabletop technology may reduce the meal duration for low-sales-ability, low-speed-ability waiters by 14.26%, a value that is 2.43% higher than for high-sales-ability, low-speed-ability waiters (11.83%), 7.09% higher than for low-sales-ability, high-speed-ability waiters (7.17%), and 9.42% higher than for high-sales-ability, high-speed-ability waiters (4.84%). All of these differences are statistically significant. In addition, the interpretations of the moderating effects in terms of the mean cutoff and the continuous case are consistent with the median cutoff case, which we omit to report in the paper for brevity.

Furthermore, we find that 57% of the checks opened by the low-sales-ability waiters (58% by the high-sales-ability ones) after the technology installation were paid with the tabletop technology . In addition, 54.58% of the checks handled by the low-speed-ability waiters (60% by the high-speed-ability ones) after the technology installation were paid with the tabletop technology. Both of these differences are statistically significant. In other words, if we use the payment method as a proxy for the technology use, we observe a slightly heavier technology use in the high-ability-waiters' checks than in the low-ability waiters' checks. The finding suggests a stronger need does not necessarily translate into action. Hence, we fail to find strong evidence for one of our hypothesized mechanisms.

In sum, the results of the moderating effects model seem to suggest that the new technology serves as a "great equalizer" – it does not necessarily make restaurant's best workers even better; rather, it reduces performance gaps among workers. The reason is likely to be that the performance improvement from technology duplicates what the high-ability workers already deliver.

Table 10: Moderating Effects by Waiters' Skill Types

	Binary *SalesSkillLevel, SpeedSkillLevel* (Median Cutoff, 1: High-Ability; 0: Low-Ability)		Binary *SalesSkillLevel, SpeedSkillLevel* (Mean Cutoff, 1: High-Ability; 0: Low-Ability)		Continuous *SalesSkillLevel, SpeedSkillLevel*	
	(1)	(2)	(3)	(4)	(5)	(6)
	log(*Sales*)	log(*MealDuration*)	log(*Sales*)	log(*MealDuration*)	log(*Sales*)	log(*MealDuration*)
System	0.0363***	-0.1426***	0.0205***	-0.1057***	0.0033**	-0.0187***
	(0.0076)	(0.0135)	(0.0043)	(0.0090)	(0.0010)	(0.0010)
SalesSkillLevel	0.0539***	-0.0316***	0.0795***	-0.0377***	0.0278***	-0.0013***
	(0.0014)	(0.0025)	(0.0032)	(0.0034)	(0.0002)	(0.0002)
System ×*SalesSkillLevel*	-0.0069***	0.0243***	-0.0109***	0.0232***	-0.0015***	0.0022***
	(0.0019)	(0.0028)	(0.0025)	(0.0032)	(0.0003)	(0.0003)
SpeedSkillLevel	0.0225***	-0.1628***	0.0243***	-0.1945***	0.0012***	-0.0181***
	(0.0014)	(0.0035)	(0.0021)	(0.0041)	(0.0001)	(0.0001)
System×*SpeedSkillLevel*	-0.0113***	0.0709***	-0.0075***	0.0713***	-0.0004***	0.0002*
	(0.0021)	(0.0036)	(0.0021)	(0.0042)	(0.0001)	(0.0001)
PartySize	0.3178***	-0.0075***	0.3172***	-0.0075***	0.3158***	-0.0065***
	(0.0021)	(0.0012)	(0.0020)	(0.0010)	(0.0002)	(0.0003)
log(*MealDuration*)	0.1990***		0.2040***		0.2110***	
	(0.0039)		(0.0037)		(0.0006)	
log(*Sales*)		0.1882***		0.1905***		0.1908***
		(0.0032)		(0.0027)		(0.0006)
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
Adjusted R-squared	0.545	0.144	0.548	0.161	0.552	0.194

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

Table 11: Interpreting the Moderating Effects of Skill Types†

	Sales Impact		Speed Impact	
	High-Sales Ability	Low-Sales Ability	High-Sales Ability	Low-Sales Ability
High-Speed Ability	1.81%	2.5%	4.84%	7.17%
Low-Speed Ability	2.94%	3.63%	11.83%	14.26%

† Defined in terms of Median Cutoff

4.4 Post-hoc Analysis

4.4.1 Sales Action Impact

Regardless of the 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 quantify the effect of the tabletop technology on upselling and cross-selling, respectively, we estimate the following models:

$$ItemQuantity_{ic} = \alpha_0 + \alpha_1 System_i + \alpha_2 \log(MealDuration_i) + \alpha_3 PartySize_i + \alpha_5 Controls_i + \varepsilon_i \quad \forall c \tag{6}$$

$$\begin{aligned}\log(Sales_{ic}) = {} & \beta_0 + \beta_1 System_i + \beta_2 \log(MealDuration_i) + \beta_3 PartySize_i + \beta_4 ItemQuantity_{ic} \\ & + \beta_5 Controls_i + \xi_i \quad c = FBA,\end{aligned} \tag{7}$$

where $ItemQuantity_{ic}$ 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 6 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 7, 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 items sold should then be attributed to the upselling action (i.e., selling more expensive items).

Table 12 shows the results of cross-selling and upselling actions. Interpreting the coefficients of *System* in Columns 1 through 5, the 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 items 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 substitute 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 of food and beverage items directly from the table. Finally, in Column 6, the coefficient of *System* is 0.0204, which implies that the 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 7, excluding the control *ItemQuantity* 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 12: Sales and Meal Duration Effects Explained by Upselling and Cross-selling Actions

	(1) *ItemQuantity* c = All†	(2) *ItemQuantity* c = FBA	(3) *ItemQuantity* c = F	(4) *ItemQuantity* c = B	(5) *ItemQuantity* 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)
ItemQuantity 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
Adjusted R-squared	0.465	0.415	0.462	0.180	0.050	0.678

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

†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).

4.4.2 Restaurant-Oriented Impact

One might suspect that the new technology may affect restaurants' staffing decisions and traffic, 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 or traffic are driving the main results. We explicitly test the management-related performance indicator of staffing levels and restaurant traffic. 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. We finally analyze the effect of the tabletop on the store traffic in terms of the number of checks opened per hour and the moderating effect of the busy hours. That is,

$$\log(HrWaiters_{rh}) = \alpha_0 + \alpha_1 System_{rh} + \alpha_2 \log(HrTables_{rh}) + \alpha_3 Controls_{rh} + \varepsilon_{rh},$$

$$\log(HrWaiters_{rh}) = \beta_0 + \beta_1 System_{rh} + \beta_2 System_{rh} \times HighStaffing_r + \beta_3 \log(HrTables_{rh}) + \beta_4 Controls_{rh} + \xi_{rh}, \quad (8)$$

$$\log(HrTables_{rh}) = \gamma_0 + \gamma_1 System_{rh} + \gamma_2 Controls_{rh} + \tau_{rh},$$

$$\log(HrTables_{rh}) = \theta_0 + \theta_1 System_{rh} + \theta_2 System_{rh} \times Busy_{rh} + \theta_3 Busy_{rh} + \theta_4 Controls_{rh} + \omega_{rh} \quad (9)$$

where $HrWaiters_{rh}$ and $HrTables_{rh}$ are the number of waiters working and the number of checks opened during hour h at restaurant r, respectively. For the moderating effect in Model 8, we follow Lu et al. (2017), who study how the effect of a computerized provider order entry system on nursing home staffing decisions depends on the vertical position of the nursing home, and we define $HighStaffing_r$ as a binary variable which is equal to 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 8 because it is time-invariant and absorbed into the restaurants' fixed effects in $Controls_{rh}$. For the moderating effect in Model 9, we create a binary variable *Busy,* which is equal to one for all the checks opened between noon and 1pm, and between 6pm and 8pm, and zero otherwise.

Table 13 shows the results of restaurant-oriented impact. Similar to the results reported in Lu et al. (2017), the coefficients of *System* turn out to be statistically insignificant in the two staffing models (0.0063 and 0.0097 in Columns 1 and 2). The interaction term is also insignificant (-0.0095). These results suggest that the implementation of the tabletop technology did not seem to affect the staffing levels on average or even depending on pre-installation staffing levels. In other words, the substitution effect of technology may cancel out the complementary 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 elected to stay with their regular staffing levels on average.

The unchanged staffing level may also be attributed to possible stable traffic. The coefficients of *System* indeed turn out to be statistically insignificant in the two traffic models (0.003 and 0.0106 in Columns 3 and 4). Its interaction term is also insignificant (-0.032). These results imply that the implementation of the tabletop technology did not seem to affect the store traffic either, which is against our expectation. The restaurants seemed to be unable to increase the table turns even though the technology reduced the meal duration by 10% on average. The reasons are speculative and anecdotal. For example, we noticed that the waiters were not particularly proactive in clearing the tables. In addition, although customers waited in line during busy hours, our focal restaurants were not packed all the time. The kitchen capacity may remain unchanged and become the bottleneck.[4] It is also plausible that the hosts were not immediately aware of when the tables were ready. Ideally, we would need customer waiting time data and kitchen workload data to understand why the table turns remain constant. We suggest that the restaurants should note that reduced meal duration does not necessarily translate to more table turns, and they should take advantage of the reduced meal duration to effectively increase table turns.

To summarize, both the unchanged staffing levels and the store traffic rule out alternative explanations of our main results and instill more confidence in our quasi-experimental setting of the technology implementation.

4.5 Further Managerial Consideration

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

[4] Kitchen staff can tell the hosts to hold, so that they cannot seat more customers.

Table 13: Restaurant-Oriented Impact

	(1) log(*HrWaiters*)	(2) log(*HrWaiters*)	(3) log(*HrTables*)	(4) log(*HrTables*)
System	0.0063	0.0097	0.0030	0.0106
	(0.0064)	(0.0073)	(0.0091)	(0.0109)
System ×*HighStaffing*		-0.0095		
		(0.0106)		
Busy				0.8827***
				(0.0220)
System×*Busy*				-0.0327
				(0.0166)
log(*HrTables*)	0.6061***	0.6060***		
	(0.0041)	(0.0041)		
Controls	Yes	Yes	Yes	Yes
Observations	215,532	215,532	215,532	215,532
Adjusted R-squared	0.807	0.807	0.291	0.093

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

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) translates into \$6 million per month for a restaurant chain that generates approximately \$200 million in revenues per month. If we use the total effect of 1%, the sales lift is \$2 million. 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. We assume the focal chain pays the entire 99 cents$\approx$ 1 dollar as a conservative approximation. In addition, the flat fee is paid only once for the entire party at the table. Furthermore, one in every 10 parties 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 technology cost is approximately $(20$ million customers $/2$ customers per party$) \times 0.1 \times \$1 = \$1$ million dollars. With the \$6 million sales lift (direct effect) or the \$2 million sales increase (total effect), the profit of the technology is estimated to be \$5 million or \$1 million. Whether \$5 million or \$1 million, this additional profitability is substantial for casual dining companies because of their traditionally low profit margins and ever increasing competition both within the sector and from the growing fast-casual dining sector. Admittedly, strong competition from late adopters of tabletop technology may lower the returns 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 data 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 sales effort (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 lift its capacity and allow more customers to be seated. 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.

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 the tabletop technology on restaurant performance. We find that the tabletop system may increase the average sales per check by approximately 1% and reduce the meal duration by approximately 10%. We further estimate that the 1% sales lift per check may translate into $2 million extra sales or $1 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 from this technology. 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 supplement capacity-constrained roles.

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 relatively short-term effects, 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 understand how to manage the company's relationships with individual customers. Third, although collecting data from one restaurant chain in one metropolitan area makes business model, geolocational and macroeconomic trends comparable across the restaurants, it remains interesting to examine the effect of similar tabletop technology in other settings, such as fine dining and airports. Fourth, we cannot directly evaluate the effect of tabletop technology on customer satisfaction. Although tips can reflect service quality and customer satisfaction, we find the ratio between the tips and the check size remains stable. The technology may have increased the tips by only 1%, a 0.0018 increase from the current sample mean of 18%. On the one hand, a self-service technology reduces the human service interaction, which may lower tips. On the other hand, some customers may be more satisfied with the efficient service which does not require them to wait for the waiters to settle the check, and tip more. Tipping is also considered a social norm in the United States, so people may continue using their heuristics of calculating how much to tip. Customer survey studies are needed to explicitly measure customer satisfaction. Finally, 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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Appendix

Outlier Robustness Checks We first use the full sample, which has 2,890,876 observations, without dropping any data to repeat our main analysis with clustered errors at the store and day level. Then we drop the observations that are four standard deviations away from the sample means. In particular, we first exclude the observations whose check size was four standard deviations (16.24 in the original distribution) above the sample mean (30.45). In doing so, we lose 11,847 observations (0.4%). We do not drop any observations less than four standard deviation below the sample mean because the check size distribution is highly skewed to the right. After that, we exclude the observations with party size that is four standard deviations (1.05 in the original distribution) above the sample mean (1.97), which removes an additional 1,194 observations (0.04%). We do not drop any observations less than four standard deviations below the sample mean also because the party size distribution is highly skewed to the right. We stop dropping extra data because after dropping the outliers in terms of check size and party size, the ranges of the rest of the variables are all within the four standard deviations around their original sample means. In other words, we essentially remove those outliers of big parties whose check size and meal duration are disproportionately large. In the end, the trimmed data set has 2,877,835 observations, which retains 99.54% of the full sample size.

Column 1 through 3 in Table 14 show the main results estimated from the full sample, while Columns 4 through 6 in Table 14 present the main results estimated from the reduced sample. The coefficients of *Systems* in the sales models (Columns 1 and 4) are equal to 0.0227 and 0.0226, which are similar to 0.0288, our main result with top and bottom 5% observations dropped. Similarly, the coefficients of *Systems* in the meal duration models (-0.127 and -0.1277) and in the sales productivity models (0.129 and 0.1298) are also similar to the main results reported (-0.0994 and 0.1077).

Additional Parallel Trends Checks

Table 14: Check-level Impact of Tabletop Technology on Restaurant Performance

	(1) log(*Sales*)	(2) log(*MealDuration*)	(3) log(*Sales/MealDuration*)	(4) log(*Sales*)	(5) log(*MealDuration*)	(6) log(*Sales/MealDuration*)
System	0.0227***	-0.1270***	0.1290***	0.0226***	-0.1277***	0.1298***
	(0.0025)	(0.0071)	(0.0071)	(0.0025)	(0.0071)	(0.0071)
log(*Sales*)		0.4257***			0.4282***	
		(0.0065)			(0.0063)	
log(*MealDuration*)	0.1521***			0.1505***		
	(0.0020)			(0.0020)		
PartySize	0.3245***	-0.0253***	0.2222***	0.3287***	-0.0243***	0.2229***
	(0.0019)	(0.0010)	(0.0026)	(0.0021)	(0.0011)	(0.0028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
H1 Supported	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,890,876	2,890,876	2,890,876	2,877,835	2,877,835	2,877,835
Adjusted R-squared	0.562	0.133	0.154	0.556	0.132	0.148

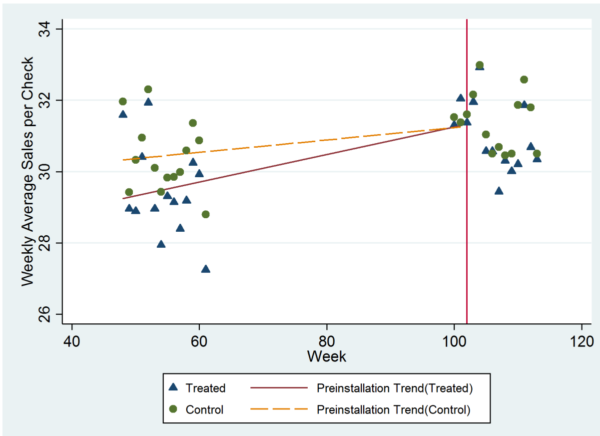
1. Clustered standard errors at store and day level are provided in parentheses. 2. *p≤ .05, **p≤ .01, ***p≤ .001.

Additional Visual Checks for Another Two Installation Months We conduct additional visual checks for the installation that happened in December, 2013 (102th week) and Feb, 2014 (111th week), respectively. Figures 4a and 4b show the average weekly sales and meal duration per check before and after the 102th week. Two restaurants installed the technology during 102th week (the treated group), while 51 restaurants had not (the control group). Although the two fitted linear trends do not appear completely parallel, they are not drastically different. More importantly, we estimate the weekly growth rates of the two groups of restaurants prior to the 102th week, whose sales and meal duration results are presented in Table 15a. Both the sales and meal duration growth rates are actually statistically indistinguishable, which supports the parallel trends assumption.

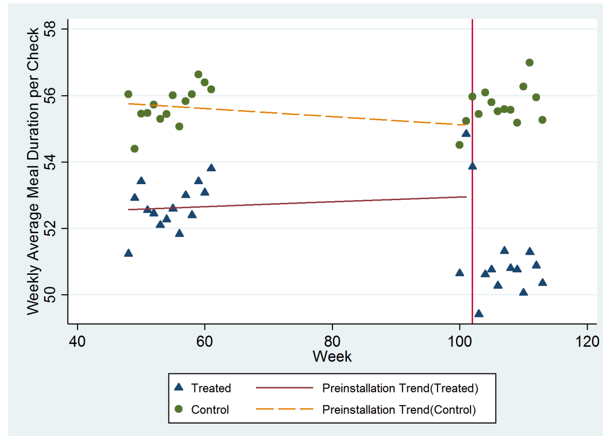
In addition, Figures 4c and 4d show the average weekly sales and meal duration per check before and after the 111th week. Then another two restaurants installed the technology (the treated group), while 42 restaurants had not (the control group). The two fitted linear trends seem to be quite parallel to each other, which provides some visual support of the parallel trends assumption. Moreover, we re-estimate the weekly growth rates of the restaurants prior to the 111th week. Table 15b presents the results. Similar to the 102th week results, both the sales and meal duration growth rates turn out to be statistically indifferentiable. These results further support our parallel trends assumption.

Figure 4: Additional Parallel Trends Checks

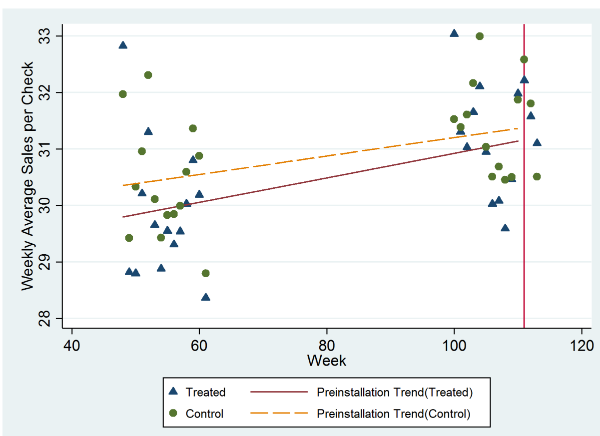
(a) Average Weekly Sales Per Check (Installation: 102th Week)



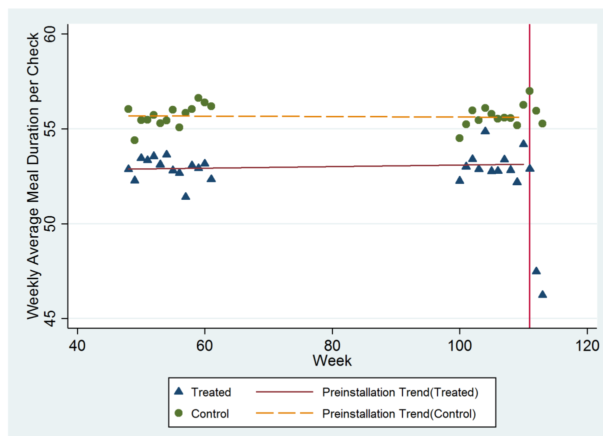
(b) Average Weekly Meal Duration Per Check During Periods I and II



(c) Average Weekly Sales Per Check (Installation: 111th Week)



(d) Average Weekly Meal Duration Per Check (Installation: 111th Week)



Optimal Full Matching

1. We select four matching variables *PreAvgSales*, *PreAvgMealDuration*, *PreAvgTables,* and *PreAvgStaffing* because we a priori postulate that restaurants may consider these factors when deciding where to implement the tabletop technology first. The technology is directly related to improving sales and efficiency, which these four variables measure.

2. We then use the four matching variables to estimate both a logit model and a probit model of the

Table 15: Weekly Growth Rates during Periods I and II

(a) Installation: 102th Week

	log(*Sales*) Treated	log(*Sales*) Control	log(*MealDuration*) Treated	log(*MealDuration*) Control
WeekTrend	0.0011*	0.0007**	0.0006	0.0001
	(0.0000)	(0.0002)	(0.0006)	(0.0001)
PartySize	0.3353*	0.3295***	0.0526**	0.0528***
	(0.0190)	(0.0027)	(0.0006)	(0.0009)
Controls	Yes	Yes	Yes	Yes
Observations	29,732	786,338	29,732	786,338
Adjusted R-squared	0.530	0.516	0.093	0.085

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

(b) Installation: 111th Week

	log(*Sales*) Treated	log(*Sales*) Control	log(*MealDuration*) Treated	log(*MealDuration*) Control
WeekTrend	0.0008	0.0005**	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
PartySize	0.3354**	0.3300***	0.0546	0.0537***
	(0.0026)	(0.0025)	(0.0050)	(0.0008)
Controls	Yes	Yes	Yes	Yes
Observations	44,473	1,041,095	44,473	1,041,095
Adjusted R-squared	0.535	0.520	0.055	0.084

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

decision to install the technology in January, 2014. As shown in Table 6, only the coefficient of *PreAvgMealDuration* is statistically significant and negative in the probit model. The results suggest that the treatment restaurants are generally comparable with the control restaurants, which supports the exogenous installation timing assumption. Nevertheless, those restaurants that tended to have shorter meal duration may have been more likely to implement the technology in January 2014 than those that had longer meal duration. We therefore apply matching to reduce such heterogeneity, and calculate the propensity score as the fitted value from the logit regression.

3. Although many matching methods are available, we use the optimal full matching algorithm [5] because 1) it minimizes the weighted average of the propensity score between each treated restaurant and each control restaurant in a subclass; 2) it does not have to discard any unmatched observations; 3) full

[5] We thank an anonymous referee for making this suggestion.

matching can reduce more bias than other matching techniques, such as nearest neighbor matching. The optimal full matching algorithm finds seven subclasses, each of which contains one treatment restaurant. The seven subclasses have 26, 3, 6,2, 2, 4, and 1 control restaurants in them, respectively.

4. After matching, we check the balance to compare the percent reduction in bias achieved with the nearest neighbor algorithm and the optimal full matching algorithm. As can be seen, the optimal full matching has higher balance improvement than the nearest neighbor in all matching variables except *PreAvgMealDuration.* In addition, the percent balance improvements of *PreAvgTables* and *PreAvgStaffing* are both negative (-308.18 and -1.55) for the nearest neighbor method, suggesting that the standardized mean differences between the treatment and the control groups actually increase after matching for these two variables. In other words, the nearest neighbor matching makes the two groups less similar in these two dimensions. By contrast, the percent balance improvements of all the variables is positive for the optimal full matching method, suggesting the optimal full matching algorithm makes two groups more similar in all dimensions. Furthermore, we conduct the omnibus test for balance of all of the four matching variables simultaneously. The p-value turns out to be 0.136, which suggests that we fail to reject the null hypothesis that states that these treatment restaurants and their matched controls are indifferentiable in terms of the four matching variables overall (i.e., the data are balanced).

Table 16: Percent Balance Improvement in Terms of Standardized Mean Difference

	Nearest Neighbor (n = 3)	Optimal Full Matching
PreAvgSales	60.31	98.26
PreAvgMealDuration	89.63	78.54
PreAvgTables	-308.18	51.19
PreAvgStaffing	-1.55	84.79

5. Finally, we repeat our difference-in-difference estimation with an interaction term between *System* (treatment) and each of the seven matched subclasses. We do not include the fixed effects of these matched subclasses because they are absorbed into the restaurant fixed effects. Table 17 shows the

results. The coefficients of *System* are all significant and have similar effect size as our main results (0.0238, -0.11 and 0.1117). These coefficients represent the effects of *System* on the treated restaurant in subclass 1, which is the biggest subclass (it has 27 out of 51 restaurants). Some of the interaction term coefficients are statistically insignificant, which suggests the treatment effects in those subclasses are indifferentiable from those in the first subclass. The significant interaction term coefficients imply heterogeneous effect sizes across these subclasses. For example, the coefficient of $System \times SubClass2$ in Column 2 is 0.0156, which suggests that the tabletop technology may reduce the meal duration by $(0.11 - 0.0156 \approx)9\%$ in subclass 2. Nevertheless, these subclasses are much smaller than subclass 1. In addition, none of these subclasses have qualitatively different results from our main analysis. Hence, we conclude that this robustness check after full matching provides congruent results with those main results without matching.

Table 17: Check-level Impact of Tabletop Technology on Restaurant Performance on a Matched Sample

	(1) log(*Sales*)	(2) log(*MealDuration*)	(3)log(*Sales/MealDuration*)
System	0.0238***	-0.1100***	0.1117***
	(0.0021)	(0.0047)	(0.0054)
System×*SubClass*2	-0.0073	0.0156*	-0.0191
	(0.0057)	(0.0071)	(0.0112)
System×*SubClass*3	-0.0012	-0.0081	0.0057
	(0.0037)	(0.0107)	(0.0128)
System×*SubClass*4	-0.0138***	0.0655***	-0.0662***
	(0.0022)	(0.0033)	(0.0045)
System×*SubClass*5	-0.0207***	0.0675***	-0.0736***
	(0.0025)	(0.0044)	(0.0053)
System×*SubClass*6	0.0082	0.0181***	-0.0082
	(0.0043)	(0.0030)	(0.0056)
System×*SubClass*7	-0.0172***	0.0200***	-0.0311***
	(0.0016)	(0.0033)	(0.0058)
log(*Sales*)		0.1895***	
		(0.0028)	
log(*MealDuration*)	0.1985***		
	(0.0039)		
PartySize	0.3194***	-0.0084***	0.2760***
	(0.0024)	(0.0008)	(0.0024)
Controls	Yes	Yes	Yes
H1 Supported	Yes	Yes	Yes
Observations	1,332,215	1,332,215	1,332,215
Adjusted R-squared	0.540	0.122	0.325

1. Clustered standard errors are shown in parentheses. 2. *p≤ .05,**p≤ 0.01,***p≤ 0.001

Check-level Analysis Focusing on the Installation Wave between Dec 2013 and Feb 2014 Table 18 shows the results of the robustness check on that wave of introduction between Dec 2013 and Feb 2014. The coefficient signs and sizes are consistent with the main results. In particular, the technology seems to increase sales per check by 2%, reduce the meal duration by 8.72% and increase sales per minute by 8.92%.

Table 18: Check-level Analysis Focusing on December 2013 and February 2014

	(1) log(*Sales*)	(2) log(*MealDuration*)	(3) log(*Sales/MealDuration*)
System	0.0200***	-0.0872***	0.0892***
	(0.0023)	(0.0022)	(0.0029)
log(*Sales*)		0.1895***	
		(0.0012)	
log(*MealDuration*)	0.2016***		
	(0.0012)		
PartySize	0.3193***	-0.0069***	0.2748***
	(0.0004)	(0.0005)	(0.0005)
Controls	Yes	Yes	Yes
H1 Supported	Yes	Yes	Yes
Observations	673,201	673,201	673,201
Adjusted R-squared	0.545	0.129	0.329

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

Placebo Test Using the To-Go Order Data In addition, Table 19 shows the results of the placebo test using the to-go order data. As can be seen, the coefficients of *System* are statistically insignificant, which supports that our estimates capture the main effects of the tabletop technology.

Table 19: Placebo Test Using the To-Go Order Data

	(1) log(*Sales*)	(2) log(*MealDuration*)
System	0.0013	0.0288
	(0.0028)	(0.0189)
log(*MealDuration*)	0.0460***	
	(0.0024)	
log(*Sales*)		0.2554***
		(0.0120)
PartySize	0.3193***	-0.0196***
	(0.0004)	(0.0043)
Controls	Yes	Yes
H1 Supported	No	No
Observations	720711	720711
Adjusted R-squared	0.577	0.031

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

We perform a day-level analysis and week-level analysis with errors correlated at the store level. In particular, we analyze the effect on the daily (weekly) average sales per check and the daily (weekly) average meal duration, while controlling for the average party size, and a group of fixed effects of the day of the week, the weeks, and the stores (i.e., *D_Controls*). The week-level analysis controls for the fixed effects of the weeks and the stores (i.e., *W_Controls*). Table 20 shows the results. The coefficients of *System* are significant and equal to 0.021 and -0.0977. The coefficient sizes are consistent with the check-level and the hour-level analyses.

Table 20: Day-Level and Week-Level Analyses

(a) Day-Level Analysis

	(1) log(*DailyAvgSales*)	(2) log(*DailyAvgMealDuration*)
System	0.0210***	-0.0977***
	(0.0021)	(0.0061)
log(*DailyAvgSales*)		0.2581***
		(0.0211)
log(*DailyAvgMealDuration*)	0.1214***	
	(0.0131)	
DailyAvgPartySize	0.4123***	-0.0080
	(0.0098)	(0.0094)
log(*DailyTables*)	0.0107	0.0447***
	(0.0055)	(0.0064)
D_Controls	Yes	Yes
Observations	17,813	17,813
Adjusted R-squared	0.870	0.680

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

(b) Week-Level Analysis

	(1) log(*WeeklyAvgSales*)	(2) log(*WeeklyAvgMealDuration*)
System	0.0117***	-0.0904***
	(0.0017)	(0.0030)
log(*WeeklyAvgSales*)		0.1086**
		(0.0394)
log(*WeeklyAvgMealDuration*)	0.0262**	
	(0.0095)	
WeeklyAvgPartySize	0.3837***	0.0393
	(0.0072)	(0.0210)
log(*WeeklyTables*)	-0.0050	0.0146
	(0.0041)	(0.0083)
W_Controls	Yes	Yes
Observations	2,772	2,772
Adjusted R-squared	0.911	0.840

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